Financial Intermediaries and the Macroeconomy: Evidence from a High-Frequency Identification*

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Abstract

We provide empirical evidence on how news about financial intermediaries' net worth impacts the aggregate economy, using a high-frequency identification strategy. We measure "financial shocks" based on the idiosyncratic stock-price changes of large U.S. intermediaries in a narrow window around their earnings announcements. We document significant effects of these shocks on the stock price and borrowing costs of nonfinancial firms, as well as on macroeconomic variables. The effects are more pronounced for firms with low credit ratings and when the aggregate net worth of intermediaries is low.

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1. Introduction

What role do financial intermediaries play in macroeconomic fluctuations? A large body of theoretical work shows that contractions in intermediaries' net worth reduce the supply of credit in the economy, leading to declines in economic activity, investment, and asset prices (see, for example, Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014, and references therein). Empirically measuring these aggregate effects is challenging because common factors affect both intermediaries' net worth and macroeconomic outcomes, and intermediaries' net worth endogenously responds to changes in macroeconomic conditions.

In this paper, we propose a high-frequency identification strategy to study the effects of changes in intermediaries' net worth on the macroeconomy. The key idea of our approach is to focus on idiosyncratic changes in the market value of large intermediaries' net worth within a narrow window around their earnings announcements. By doing so, we build on two key strands of macroeconomic identification. First, in the spirit of the high-frequency approach to studying the effects of monetary policy shocks (surveyed in Ramey, 2016; Nakamura and Steinsson, 2018a), we exploit the discontinuity in the information released about intermediaries' net worth caused by their earnings announcements. Second, by focusing on large financial intermediaries, we draw on the literature that leverages granular variation from idiosyncratic shocks to large economic players to estimate aggregate effects (see, for example, Gabaix and Koijen, 2020).

Our empirical analysis focuses on the earnings announcements of U.S. commercial banks, investment banks, and securities dealers included in the S&P 500 Index from 1998 to 2020. We begin by studying the stock market's reaction to these earnings announcements using tick-level stock price data from the New York Stock Exchange's Trade and Quote database for S&P 500 constituents. For each earnings announcement, we measure the releasing intermediary's stock price change in a narrow window around the event. We refer to this variable as a "broad financial shock," as it measures the changes in a financial intermediary's market value of net worth induced by all information disclosed during its earnings announcement. Using an event-study framework, we document that a broad financial shock equivalent in size to a 1% change in the market value of the financial intermediaries in our sample is associated with a 0.25% change in the stock price of nonfinancial firms within a narrow window (60 minutes) around intermediaries' earnings announcements. We complement these estimates with those from a heteroskedasticity-based identification—which allows for common factors affecting the stock prices of intermediaries and nonfinancial firms, as well as simultaneity between these variables—and find a larger estimated elasticity of nonfinancial firms' stock prices to intermediaries' stock prices compared to the event-study framework. In bond markets, we find that positive financial shocks are associated with lower spreads for high-risk nonfinancial firms' bonds and a lower excess bond premium (Gilchrist and Zakrajšek, 2012).

The asset price reactions to intermediaries' earnings announcements that we document can, in principle, reflect not only information about intermediaries' net worth but also information about nonfinancial firms' conditions (e.g., their productivity or demand). We present two pieces of evidence on the role of information about intermediaries' net worth in driving our empirical results. First, we use security-level data on bond holdings of each financial institution and show that, within a firm, bonds with more substantial holdings by an earnings-releasing intermediary exhibit a larger sensitivity, in absolute value, to broad financial shocks. This result rejects the null hypothesis that the estimated reaction of nonfinancial firms' bond prices to intermediaries' earnings announcements is purely driven by information about nonfinancial firms' conditions, and is consistent with intermediaries' announcements containing information about their net worth (see Morelli, Ottonello and Perez, 2022).

Second, building on methods developed to purge monetary surprises from information channels (e.g., Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020), we use sign restrictions to construct "purged financial shocks," which isolate the component of broad financial shocks that reflects changes in credit supply. This approach filters out the component of financial shocks that contains information related to nonfinancial firms' conditions, which may be revealed during intermediaries' earnings announcements. Specifically, we identify purged financial shocks as the component of broad financial shocks that negatively comoves with changes in the excess bond premium. This negative comovement is consistent with the predictions of models with frictional intermediaries for news about intermediaries' net worth, which leads to opposite effects on the intermediation premium through its impact on credit supply. We show that using purged financial shocks results in an estimated elasticity of nonfinancial firms' stock prices to the releasing intermediary's stock prices that is twice as large as when using broad financial shocks, implying that information about intermediaries' net worth revealed during these announcements has a significant effect on the stock prices of nonfinancial firms.

Finally, we study the transmission channels of financial shocks and their impact on macroeconomic variables. For the transmission of financial shocks, we find that their effects are stronger during periods when the aggregate net worth of the financial system is low. This state dependency suggests that the overall health of the financial system is a key driver of the aggregate effects of intermediaries, as emphasized in theoretical models motivating our paper and in the broader literature on financial crises (e.g., Reinhart and Rogoff, 2009; Bernanke, 2018; Gertler and Gilchrist, 2018). Additionally, we show that firms facing more severe financial frictions—such as those with lower credit ratings—are more affected by financial shocks, indicating that firms' financial positions play a critical role in the transmission of these shocks (as highlighted, for example, in Khan and Thomas, 2013; Jermann and Quadrini, 2012; Christiano, Motto and Rostagno, 2014).

To study how financial shocks affect macroeconomic variables, we turn to monthly data and use an external-instrument vector autoregression (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015). We find that financial shocks have sizable and persistent effects on industrial production, unemployment, borrowing costs, and aggregate uncertainty. Compared with impulse responses identified using the Cholesky decomposition, those identified with high-frequency financial shocks as the external instrument are more conservative and precisely estimated.

Our findings are consistent with a large body of empirical work that provides evidence that the net worth of financial intermediaries affects nonfinancial firms (e.g., Khwaja and Mian, 2008; Amiti and Weinstein, 2011; Chodorow-Reich, 2014) and asset prices (e.g., Coval and Stafford, 2007; Adrian, Etula and Muir, 2014; He, Kelly and Manela, 2017; Siriwardane, 2019; and He and Krishnamurthy, 2018 for a recent survey). An important element in the identification strategy developed in this body of work is the cross-sectional exposure of firms or assets to intermediaries. Our paper complements this literature by documenting financial intermediaries' aggregate effects. To date, empirical work on these aggregate effects has used time-series methods (see, for example, Gilchrist and Zakrajšek, 2012; Stock and

Watson, 2012; Jordà, Schularick and Taylor, 2013; Krishnamurthy and Muir, 2017; Brunnermeier, Palia, Sastry and Sims, 2021; Baron, Verner and Xiong, 2021); regional data (Huber, 2018; Gertler and Gilchrist, 2019); and model-based inference (see, for example, Christiano, Eichenbaum and Trabandt, 2015; Herreño, 2020).

We consider our high-frequency strategy to be complementary to prior empirical work, contributing to the literature along two dimensions. First, high-frequency methods tend to require milder assumptions for the identification of aggregate effects (as discussed, for instance, in Nakamura and Steinsson, 2018b).[1] Second, our high-frequency financial shocks can be used directly by other researchers conducting empirical research on macroeconomics, similar to the large body of evidence developed using high-frequency monetary policy shocks. This can be particularly useful to discipline models aimed at understanding the role of financial intermediaries in determining the aggregate transmission of shocks.

2. Data

Our empirical analysis uses tick-by-tick data on intermediaries' stock prices in a window around their earnings releases. We obtain tick-level stock prices from the New York Stock Exchange's Trade and Quote (TAQ). The TAQ database contains intraday trades time-stamped to the second for all securities listed on the New York Stock Exchange, American Stock Exchange, Nasdaq, and SmallCap issues. We collect earnings announcements' precise dates and times from the Institutional Brokers' Estimate System (IBES). Our baseline sample focuses on the commercial banks, investment banks, and securities dealers included in the S&P 500 Index during the period 1998 to 2020.[2] We focus on these types of intermediaries because their direct involvement in financial activities in the economy renders them more likely to be linked to the macroeconomy, which is our main focus of analysis. Table 1 details the set of 18 financial intermediaries selected based on our main criteria, together with the period in which they are included in our analysis. Table 1 also shows that financial

[1] For additional work using the high-frequency approach to study the effect of monetary policy shocks in the economy, see Cook and Hahn (1989), Kuttner (2001), Cochrane and Piazzesi (2002), Gürkaynak, Sack and Swanson (2004), Bernanke and Kuttner (2005), and Gorodnichenko and Weber (2016), among others.

[2] We start the sample in 1998, when precise time stamps in IBES became available. The financial intermediaries we use in the analysis correspond to NAICS 522110 and 523110, which are included in the S&P 500 consecutively for at least 10 years to focus on a balanced sample, and we exclude regional banks (GICS 40101015) to focus on granular intermediaries.

Table 1: Financial Intermediaries Included in the Sample

Financial Intermediary	Ticker	Start	End	Avg Equity ($ billion)	Share of Sample	Share of Aggr Equity
Bank of America	BAC	1998Q1	2020Q4	170.0	21.7%	12.6%
Citicorp	CCI, C	1998Q1	2020Q4	164.7	21.1%	12.2%
J.P. Morgan Chase	CMB, JPM	1998Q1	2020Q4	151.5	19.4%	11.2%
Wells Fargo	WFC	1998Q1	2020Q4	105.5	13.5%	7.8%
Goldman Sachs	GS	2002Q3	2020Q4	51.7	3.6%	3.9%
Morgan Stanley	MWD, MS	1998Q1	2020Q4	48.5	6.2%	3.6%
Wachovia	WB	1998Q1	2008Q4[a]	35.8	2.2%	4.0%
U.S. Bankcorp	USB	1998Q1	2020Q4	29.2	3.7%	2.2%
Merrill Lynch	MER	1998Q1	2008Q4[b]	25.4	1.6%	2.8%
Bank of New York Mellon	BK	1998Q1	2020Q4	24.4	3.1%	1.8%
Bank One	ONE	1998Q1	2004Q2[c]	19.8	0.7%	3.0%
FleetBoston	FBF	1998Q1	2004Q1[d]	14.9	0.5%	2.3%
Lehman Brothers	LEH	1998Q1	2008Q3	12.6	0.8%	1.4%
Jefferies	JEF	2018Q3	2020Q4	8.9	0.1%	0.4%
First Chicago	FCN	1998Q1	1998Q4[e]	8.2	0.0%	1.5%
Ameriprise	AMP	2005Q4	2020Q4	7.7	0.7%	0.5%
MBNA Corp	KRB	1998Q1	2005Q4[f]	7.6	0.3%	1.0%
Northern Trust	NTRS	1998Q1	2020Q4	6.0	0.8%	0.4%
BankBoston	BKB	1998Q1	1999Q3[g]	4.9	0.0%	0.9%
Mean				47.2	5.26%	3.87%
SD				56.4	7.58%	4.02%
Min				4.9	0.02%	0.42%
Max				170.0	21.75%	12.59%
Total				897.2	100.00%	73.62%

Notes: This table lists the financial intermediaries included in the sample and their tickers in the TAQ. "Avg Equity" is the time-series average of total shareholder equity of the financial intermediary. "Share of Sample" measures a financial intermediary's equity as a share of the equity of all financial intermediaries in the sample. "Share of Aggr Equity" represents a financial intermediary's equity as a share of the aggregate equity of U.S. depository institutions. [a]Acquired by Wells Fargo. [b]Acquired by Bank of America. [c]Merged with J.P. Morgan Chase. [d]Acquired by Bank of America. [e]Merged with Banc One to form Bank One. [f]Acquired by Bank of America. [g]Merged with Fleet to form FleetBoston.

intermediaries in our sample represent 67% of the total equity of U.S. depository institutions, measured by the Federal Reserve's Flow of Funds. Therefore, our sample is based on large financial institutions, whose individual changes in net worth are likely to represent a significant change in the net worth of the entire financial sector.[3] In our period of analysis, we obtain 870 announcements of earnings, with roughly four per institution–year.

Our analysis also uses stock- and bond-price data of nonfinancial firms. For stock prices, we use intraday data on the S&P 500 constituent securities, also obtained from the TAQ

[3]Gabaix and Koijen (2020) discuss how idiosyncratic shocks to large players in the economy that affect aggregates constitute powerful instruments. Appendix A discusses the importance of granularity for identifying the effects of financial shocks in an illustrative theoretical framework.

database. Our main analysis focuses on the movements of these nonfinancial constituents in the same narrow window as that of financial intermediaries. We complement this analysis with additional daily indices data from FRED and Bloomberg—the S&P 500 Ex-Financials, S&P SmallCap 600, and Russell 2000 indices. Appendix Table B.1a presents descriptive statistics of daily stock returns in our period of analysis and shows that days with financial shocks exhibit descriptive statistics similar to those of the whole period of analysis.

For bond prices, we use data from several sources. First, we use daily data on U.S. corporate bond indices from the Intercontinental Exchange Bank of America (ICE BofA), obtained from FRED.[4] Our analysis covers a wide range of ratings from investment grade to high yield. Second, we use data on the "excess bond premium," developed by Gilchrist and Zakrajšek (2012) and extended to daily frequency by Gilchrist, Wei, Yue and Zakrajšek (2021), which measures risk premia as the residuals from projecting firms' bond spreads on their probabilities of default using Merton's 1974 model. Third, to study the within-firm variation of bond prices, we use individual bond-level data from the constituents of corporate bond indices. For each of these bonds, we have information on option-adjusted spreads and bond characteristics from the ICE BofA; transaction-level data in the secondary market from the Trade Reporting and Compliance Engine (TRACE); and the share of bonds (at CUSIP level) held by each reporting financial institution from Bloomberg. Appendix Tables B.1b and B.2 report descriptive statistics for bond data.

3. Asset Price Reactions to Intermediaries' Earnings Announcements

This section studies the asset price reaction to intermediaries' earnings announcements using a high-frequency approach. Section 3.1 focuses on characterizing changes in releasing intermediaries' stock prices, which provides the basis for our measures of financial shocks. Section 3.2 documents nonfinancial firms' stock price reactions to intermediaries' earnings announcements, and Section 3.3 examines the reactions of bond spreads.

[4] The choice of daily frequency takes into account the less liquid nature of bond markets as well as the day-end settlement time of major participants (such as mutual funds).

3.1. High-frequency measures of financial shocks

For each earnings announcement, we measure the releasing intermediary's stock price change in a narrow window around the event. Our baseline analysis focuses on announcements made during trading hours, in a window of 20 minutes before the announcement and 40 minutes after, following Nakamura and Steinsson (2018b) for monetary policy shocks.[5] We refer to this variable as a "broad financial shock," as it measures changes in a financial intermediary's market value of net worth induced by all information disclosed during its earnings announcement. In Section 4.2, we construct a measure of "purged financial shocks," using sign restrictions to isolate the component of these stock price changes that reflects changes in credit supply, filtering out information related to nonfinancial firms' conditions disclosed during intermediaries' earnings announcements.

Table 2 reports a set of descriptive statistics on broad financial shocks. The first column reports that, on average, the change in the log stock price of reporting institutions is close to zero, with a standard deviation of 2.5%, and median positive and negative values close to 1%. To more easily interpret the magnitude of these changes in terms of the market value of the intermediaries in our sample, the second column reports descriptive statistics when we scale each change in the log price of reporting institutions by their market share, i.e., $v_{\mathrm{F},t} \equiv \theta_{i,q(t)} \Delta p_{\mathrm{F},i,t}$, where $\theta_{i,q(t)}$ denotes the market capitalization of institution i as a share of the total market capitalization of all institutions in our sample, measured in the quarter $q(t)$ before the announcement. Scaling reduces the magnitude of the shocks overall, resulting in a standard deviation of 0.30% and median positive and negative values of 0.06% and −0.08%, respectively.

Appendix C conducts a set of exercises to examine the content of broad financial shocks. First, Appendix C.1 uses data on unexpected earnings in announcements to show that stock price movements of releasing intermediaries tend to be positively associated with their earnings surprises, suggesting that financial shocks encode the information released in the earn-

[5] Intraday data from the TAQ are available during the Consolidated Tape System's hours of operation, which were 8:00–18:30 Eastern Time as of August 2000 and 4:00–18:30 Eastern Time as of March 2004. For robustness checks, or when using daily data, we also consider the sample of intermediaries' earnings announcements made outside of trading hours. In these cases, we measure stock price changes between closing and opening log prices. Appendix Figure B.1 illustrates this measurement with four graphical examples. Panels (a) and (b) show two shocks that occur during trading hours, corresponding to the median positive and negative stock price changes; Panels (c) and (d) illustrate shocks occurring outside of trading hours.

Table 2: High-Frequency Broad Financial Shocks: Descriptive Statistics

	Releasing Intermediaries Stock Price Changes		All Intermediaries Stock Price Changes	
	Unweighted	Weighted (v_{F})	Unweighted	Weighted (Δp_{F})
Mean	-0.10	-0.03	-0.20	-0.04
Median +	1.22	0.07	3.85	0.33
Median −	-1.13	-0.09	-4.94	-0.41
Std Deviation	2.48	0.28	10.57	0.85
5th Percentile	-3.92	-0.50	-14.19	-1.30
95th Percentile	3.67	0.31	13.95	1.35
Observations	523	523	523	523

Notes: This table reports descriptive statistics for stock price changes around financial intermediaries' earnings announcements, referred to as broad measures of financial shocks. Unweighted changes of a reporting financial intermediary are based on its stock price 20 minutes before and 40 minutes after its earnings announcement. Weighted stock price changes of a reporting financial intermediary, denoted as v_{F} in the main text, are weighted by the market net worth of the financial intermediary as a fraction of the total market net worth of the sample in the quarter. Stock price changes of all intermediaries are the unweighted sum of all sample intermediaries' stock price changes around reporting intermediaries' earnings releases. Weighted stock price changes of all intermediaries, which are denoted as Δp_{F} in the main text, are the weighted sum based on all sample intermediaries. "Median +" and "Median −" refer to median positive and median negative stock price changes.

ings announcements. Second, Appendix C.2 uses a state-of-the-art machine-learning model to show that financial shocks are not predictable based on macroeconomic or financial data available prior to the earnings announcement. Next, Appendix C.3 shows no systematic differences in stock price changes between the first intermediaries to report earnings and those that report subsequently. Lastly, Appendix C.4 conducts textual analyses on news articles from the *Wall Street Journal* to understand how the financial press interprets intermediaries' earnings. The textual sentiment of these news items is positively associated with earnings surprises and financial shocks, the topics covered in the news articles revolve around intermediaries' core business areas, and narratives constructed in the articles attribute stock price movements to earnings performance relative to forecasts and attribute earnings results to bank-specific factors.

Our empirical analysis also uses data on the stock price change of all intermediaries in our sample in a narrow window around an intermediary earnings announcement. Table 2 reports descriptive statistics of this variable, computed as either the unweighted sum of changes in the log prices of all sample intermediaries or the sum weighted by market share (i.e., $\Delta p_{\mathrm{F},t} \equiv \sum_{i\in\mathcal{I}_q} \theta_{i,q(t)}\Delta p_{\mathrm{F},i,t}$). Relative to the broad financial shocks based on the log stock price of the releasing intermediary, changes in the log stock price of all intermediaries are similarly centered around zero and have a greater standard deviation. To further analyze the connection between these variables, Appendix Figure B.2 reports how changes in the log market capitalization of non-releasing intermediaries relate to changes in the stock price of the releasing intermediary in subsequent days after the event. These results indicate limited comovement between the stock prices of releasing intermediaries and non-releasing intermediaries during event windows (with an estimated elasticity below 0.2), consistent with the view assigning an important role to idiosyncratic shocks driving changes in releasing intermediaries' market value of net worth around their earnings announcements.

3.2. Nonfinancial firms' stock-price reactions

Event-study framework. We begin by studying nonfinancial firms' stock-price reactions to intermediaries' earnings announcements using an event-study framework, by estimating the model:

$$\Delta y_{jt} = \alpha_j + \beta \Delta x_{\mathrm{F},t} + \varepsilon_{jt}, \tag{1}$$

where t denotes the period of an intermediary earnings announcement; $\Delta x_{\mathrm{F},t}$ denotes either $v_{\mathrm{F},t}$ or $\Delta p_{\mathrm{F},t}$; Δy_{jt} denotes the log price change of nonfinancial S&P 500 constituent stock j in the same narrow window around the earnings announcement as $\Delta x_{\mathrm{F},t}$; and ε_{jt} is a random error term. We cluster standard errors in two ways to account for potential correlation within outcomes of nonfinancial firms and within periods.

Our coefficient of interest, β, measures the elasticity of nonfinancial firms' stock prices to intermediaries' stock prices within a narrow window around intermediaries' announcements. This estimated coefficient can capture the effects of two types of news released during intermediaries' earnings announcements, which we discuss in the context of a simple framework of intermediaries facing financial frictions in Appendix A. First, intermediaries' earnings announcements may convey information about credit supply. In particular, since intermediaries in our sample are relatively large, idiosyncratic shocks affecting their net worth can have an effect on credit supply and affect nonfinancial firms' financing costs, investment decisions, and market values (e.g., Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014). In addition, announcements can reveal information about non-releasing intermediaries or financial sector-wide shocks (e.g., intermediaries' costs of raising external finance), which can also induce changes in credit supply and, through similar channels, affect nonfinancial firms. Second, intermediaries' earnings announcements may convey information about the rest of the economy. For example, information about nonfinancial firms' conditions (e.g., their future productivity or demand) can affect nonfinancial firms' market value beyond the effects induced by changes in credit supply but may still be systematically associated with the releasing intermediary's stock price and affect the estimated elasticity of nonfinancial firms' stock prices to intermediaries' stock prices. Section 4.2 conducts an event-study based on purged financial shocks, which estimates the elasticity of nonfinancial firms' stock prices to intermediaries' stock prices while filtering out the effect of nonfinancial firms' conditions disclosed during intermediaries' earnings announcements.

Table 3 reports the baseline results from estimating (1). Column (1) reports the results when we use as a regressor the change in the stock price of the releasing intermediary, $\upsilon_{\mathrm{F},t}$, indicating an estimated elasticity of nonfinancial firms' stock prices to the (scaled) releasing intermediaries' stock prices within a narrow window around earnings announcements of 0.25.[6] Column (2) reports the results when we use as a regressor the change in the log stock price of all intermediaries in our sample, $\Delta p_{\mathrm{F},t}$, with an estimated elasticity of 0.19. The fact that this estimated elasticity is smaller but relatively close to that in Column (1) stems from the limited comovement between the stock prices of releasing and non-releasing intermediaries in our sample during event windows, as documented in the previous section. Based on this, we center the rest of the event-study exercises on the estimated elasticity with respect to $\upsilon_{\mathrm{F},t}$.

Robustness. Appendix D presents a set of results showing the robustness of the event-study results to various specifications. First, Appendix Table D.1 shows that the results reported in Table 3 are robust to the use of alternative dependent variables, including the value-weighted log stock price changes of the S&P 500 nonfinancial constituents or the broad S&P 500 Index, measured through the exchange-traded fund SPDR at high frequency. Ap-

[6] Re-expressing the effects in terms of earnings surprises, we estimate in Appendix Table C.1 that earnings surprises that are one standard deviation below analysts' expectations lead to a 0.1% decline in the stock price of nonfinancial firms.

Table 3: Stock Market's Reaction to Intermediaries' Earnings Announcements

	(1)	(2)	(3)
	Event-Time		**Heteroskedasticity**
v_{F} (releasing intermediaries)	0.245**		
	(0.104)		
Δp_F (all sample intermediaries)		0.190***	0.363***
		(0.052)	(0.027)
			[0.299,0.415]
R^2	0.012	0.029	-
Observations	173,475	171,313	1,373
Security fixed effects	yes	yes	no

Notes: This table reports stock market's reaction to intermediaries' earnings announcements in 60-minute windows around intermediaries' earnings announcements. Columns 1 estimates the event-study regression in (1): $\Delta y_{jt} = \alpha_j + \beta v_{\mathrm{F},t} + u_{jt}$, where Δy_{jt} is the high-frequency log price change of a nonfinancial S&P 500 constituent stock j; $v_{\mathrm{F},t}$ is the broad financial shock; and α_j is a security (CUSIP) fixed effect. Columns 2 estimates a variant of (1): $\Delta y_{jt} = \alpha_j + \gamma \Delta p_{\mathrm{F},t} + u_{jt}$, where $\Delta p_{\mathrm{F},t} \equiv \sum_{i \in \mathcal{I}_q} \theta_{i,q(t)} \Delta p_{\mathrm{F},i,t}$ is the weighted sum of stock-price changes of all sample intermediaries around the earnings announcement of intermediary i at time t. Standard errors in Columns 1 and 2 are two-way clustered at shock and security levels and reported in parentheses. Column 3 reports the heteroskedasticity-based estimator for γ from the bivariate model (3) implemented with an instrumental variable approach. The F-statistics from the first stage is 423. Standard errors and confidence intervals are computed with stratified bootstrap, as described in the text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

pendix Table D.1 also reports estimates when changes in financial intermediaries' stock prices are not scaled by $\theta_{i,q(t)}$. The results show that a 1% change in the stock prices of earnings-releasing financial intermediaries is associated with a 0.03% change in the market value of nonfinancial firms.

Second, Appendix Table D.2 shows that the estimated elasticity is larger when using daily frequency data and when using the S&P SmallCap 600 and Russell 2000 instead of the S&P 500 Index; this finding leads us to further explore the heterogeneous transmission of financial shocks in Section 5. Third, Appendix Table D.3 shows that the estimated elasticity is larger when using a measure of financial shocks that includes announcements made outside of trading hours.[7] Fourth, Appendix Figure B.3 shows that the high-frequency shocks do not have a significant association with changes in the market value of nonfinancial firms during the days before the shock, suggesting that the baseline estimates are not driven by

[7] A related concern is that intermediaries may strategically release worse earnings outside of trading hours. Appendix Figure D.1 plots realized earnings results against the hours of earnings announcements and shows no evidence of strategic timing.

pre-trends. This figure also shows that the high-frequency shocks do not have an impact on the days following the shocks, indicating that the information in broad financial shocks is incorporated into the value of nonfinancial firms on the day of the shock, with no offsetting forces on subsequent days to reverse the impacts of these shocks.

Finally, Appendix Table D.4 accounts for systematic comovements between the stock prices of nonfinancial firms and financial intermediaries. We estimate the time-varying beta between the S&P 500 Ex-Financials and S&P 500 Financials indices in the month before the broad financial shock, remove the predicted component of the high-frequency broad financial shocks attributable to a systemic component, and use the residuals as the shock. The estimated elasticity of 0.5 is statistically significant and larger than our baseline estimate, indicating that the baseline estimates are not driven by systemic comovements.

Heteroskedasticity-based identification. We complement the estimates from the event-study framework with a heteroskedasticity-based identification strategy (developed by Rigobon, 2003; Rigobon and Sack, 2004), which allows for unobserved common shocks (unrelated to the release of earnings of intermediaries) that affect both nonfinancial firms' outcomes and financial intermediaries' stock prices in the narrow window around earnings announcements; and for feedback effects from nonfinancial firms' outcomes to financial intermediaries' stock prices. For this strategy, consider the following simultaneous-equation model (following Rigobon and Sack, 2004; Hébert and Schreger, 2017):

$$\Delta p_{\mathrm{N},t} = \alpha_{\mathrm{N}} + \gamma \Delta p_{\mathrm{F},t} + \lambda_N F_t + \varepsilon_{\mathrm{N},t}, \tag{2}$$

$$\Delta p_{\mathrm{F},t} = \alpha_{\mathrm{F}} + \eta \Delta p_{\mathrm{N},t} + \lambda_F F_t + \varepsilon_{\mathrm{F},t}, \tag{3}$$

where $p_{\mathrm{N},t}$ and $p_{\mathrm{F},t}$ are the changes in the log stock price of nonfinancial firms and financial intermediaries; F_t is an unobserved factor that affects both financial and nonfinancial market values; and $\varepsilon_{\mathrm{N},t}$ and $\varepsilon_{\mathrm{F},t}$ are shocks uncorrelated with each other, the unobserved factor, or over time. The coefficient of interest, γ, measures the impact of changes in the market value of financial intermediaries on the market value of nonfinancial firms.

Unlike the event-study framework, the heteroskedasticity-based approach uses data from both times in which intermediaries release their announcements and times in which they do not. We define events as the times in which the financial intermediaries in our sample report earnings and compare them with nonevents, defined as the times in which nonfinancial firms in the S&P 500 release earnings. For time t when either financial or nonfinancial firms release earnings, we measure $\Delta p_{\mathrm{F},t}$ with the change in the log value-weighted index of intermediaries' stock prices in a 60-minute window and $\Delta p_{\mathrm{N},t}$ with the change in the log value-weighted index of nonfinancial firms' stock prices in the same window.[8] We estimate the coefficient of interest, γ, following the instrumental variable approach developed by Rigobon and Sack (2004). Standard errors and confidence intervals use the bootstrap procedure developed by Hébert and Schreger (2017) to correct for small-sample bias.[9]

The identifying assumption for the heteroskedasticity-based identification is that the variance of intermediaries' stock prices is larger during earnings-announcement event times than in nonevent times, while those of nonfinancial firms are the same during both earnings releases of financial intermediaries and nonevent times. To validate this assumption, we report in Appendix C.5 the volatility of the stock prices of financial intermediaries and nonfinancial firms during event and nonevent windows. These moments show that the variance in financial intermediaries' stock prices during their earnings announcements increases by substantially more than that of nonfinancial firms during those events, which is consistent with the fact that intermediaries' earnings announcements contain more information about financial intermediaries than about nonfinancial firms. In contrast, variance in the stock price of nonfinancial firms remains the same during both the event times of financial intermediaries' earnings releases and nonevent times.

The third column in Table 3 shows results from the heteroskedasticity-based identification. The estimated coefficients indicate that a 1% change in the stock price of intermediaries in our sample is associated with a 0.36% change in the stock price of nonfinancial firms. The estimates obtained under the event-study approach appear to be below those obtained under the heteroskedasticity-based approach, which suggests that the stronger identifying assumptions from the event-study approach do not lead overall to an upward bias (see Rigobon and Sack, 2004, for a more detailed analysis of this comparison).[10]

[8] The 60-minute event window matches the frequency from the event-study framework.

[9] We use 1,000 repetitions of a stratified bootstrap and resample with replacement from events and nonevents.

[10] A full comparison of the two empirical strategies, for different weightings and frequencies, is reported in Appendix Table B.5.

Additional exercises. We conduct two additional exercises characterizing the stock market responses to intermediaries' earnings releases. First, we show that the stock price reactions we document in response to these announcements are not found when applying a similar procedure to the earnings announcements of nonfinancial firms. For this exercise, we follow a high-frequency procedure similar to that developed in Section 3.2 for broad financial shocks, but focus on the earnings announcements of nonfinancial firms included in the Dow Jones Industrial Average. Appendix Table B.3b shows the results of estimating the event-study regression using shocks to nonfinancial firms instead of broad financial shocks. The results yield a baseline estimate that is negative, not statistically significant, and unstable across specifications. To render the shocks further comparable, Appendix Table B.3c restricts the number of Dow Jones firms used in placebo shocks to match the number of financial intermediaries included in broad financial shocks, selecting the top nonfinancial firms by market value. Again, placebo shocks do not exhibit an effect similar to that of broad financial shocks.[11]

Furthermore, we construct high-frequency placebo shocks for each of the 10 nonfinancial sectors in the S&P 500. As in the procedure for broad financial shocks, we collect precise dates and times for nonfinancial firms' earnings releases and compute their log price changes in a narrow 60-minute window around the announcement, weighted by their market values. We estimate $\Delta \log y_t^{-s} = \alpha + \beta v_t^s + u_{st}$ for each sector $s \in \{\text{energy, materials, ...}\}$, where v_t^s is the placebo shock and y_t^{-s} is the equity index that excludes the placebo shock sector. Appendix Table B.4 reports the estimates, all of which are statistically insignificant, suggesting that the effects identified in our empirical model are specific to financial intermediaries.

Finally, our focus on large financial intermediaries motivates a natural implementation of the granular-instrumental-variable strategy (GIV, developed by Gabaix and Koijen, 2020), which provides an alternative approach for accounting for the endogeneity between intermediaries and the macroeconomy. Appendix Table D.5 estimates the effects of intermediaries' stock on nonfinancial firms' stock prices, instrumented with the GIV of the time-varying

[11]The disconnect between placebo shocks and the rest of the economy may arise from either a lack of transmission from earnings results to stock prices or a disconnect between nonfinancial firms' net worth and the rest of the economy. Appendix Table C.1 shows that the earnings surprises of placebo Dow Jones firms transmit similarly to their stock prices, as do the earnings surprises of financial intermediaries, both with an elasticity of 0.2; this indicates that the differential impacts of broad financial shocks and placebo shocks arise from their different roles in the economy.

difference between size-weighted and equal-weighted changes in intermediaries' market values. Both the magnitude and statistical significance of the estimates under the GIV strategy align with those from our baseline event-study regressions.

3.3. Nonfinancial firms' bond-spreads reactions

To study nonfinancial firms' bond-price reactions to intermediaries' earnings announcements, we estimate the Jordà's 2005-style local projections:

$$\Delta_h z_t = c_h + \beta_h v_{\mathrm{F},t} + u_t, \tag{4}$$

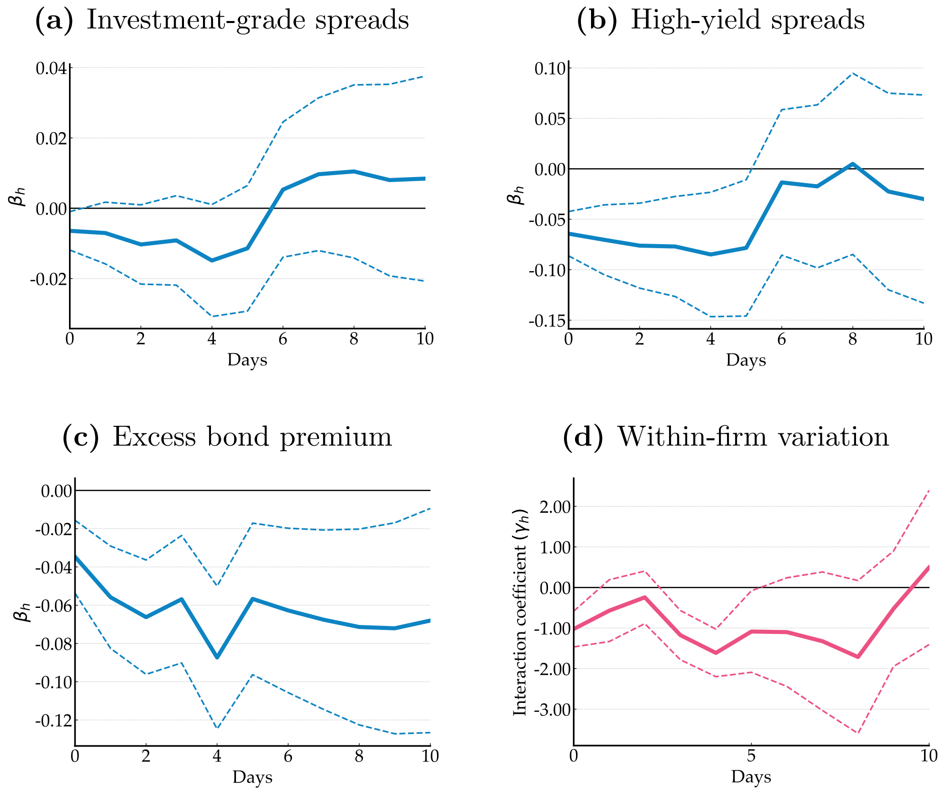
where z_t is the bond spread of interest; $v_{\mathrm{F},t}$ is the measure of broad financial shocks that includes earnings announced outside of trading hours (to match the daily frequency of bond indices); and β_h estimates the semi-elasticity of corporate bonds to broad financial shocks at horizon h.

Panels (a) and (b) in Figure 1 show that increases in the stock prices of intermediaries releasing earnings are associated with lower bond spreads for nonfinancial firms. The semi-elasticity of high-yield bond spreads is larger, with a 1% negative broad financial shock being associated with an increase of 6 to 10 basis points in these spreads. Panel (c) shows that increases in the stock prices of intermediaries releasing earnings are also associated with a lower excess bond premium, with a semi-elasticity between 0.04 and 0.08.

4. Interpreting the Effects of Intermediaries' Earnings Annoucements

As discussed in Section 3, the asset price reactions to intermediaries' earnings announcements can reflect not only information about intermediaries' net worth but also about nonfinancial firms' conditions. This section presents two pieces of evidence on the role of information about intermediaries' net worth in driving our empirical results: Section 4.1 provides evidence using within-firm variation in bond holdings by individual financial institutions, and Section 4.2 uses sign restrictions to purge nonfinancial firms' information effects from financial shocks.

Figure 1: Bond Market's Reaction to Intermediaries' Earnings Announcements



Notes: Panels (a)–(c) in this figure show the estimated cumulative responses, β_h, for horizon h from estimating local projections $\Delta_h z_t = c_h + \beta_h v_{\mathrm{F},t} + u_t$. The dependent variable, z_t, is the option-adjusted spreads for the investment-grade U.S. corporate bond index, the option-adjusted spreads for the high-yield U.S. corporate bond index, and the excess bond premium. $v_{\mathrm{F},t}$ is the measure of broad financial shocks that includes earnings announced outside of trading hours. Panel (d) reports estimates of γ_h from $\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \pi_{k(j)it} v_{\mathrm{F},t} + \Gamma' Z_{jt} + u_{jith}$, where $\Delta_h z_{k(j)it}$ is cumulative changes in bond option-adjusted spreads; $\pi_{k(j)it}$ is the holdings of bond k by intermediary i; α_{jt} is a firm-by-shock fixed effect; and Z_{jt} is a vector of bond controls including bond holdings $\pi_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, average spreads in the previous 30 days, month-to-date changes in spreads, and bid-ask spreads. Standard errors are two-way clustered at shock and firm level. Dashed lines represent 90% confidence intervals.

4.1. Within-firm bond-level evidence

We begin by considering a strategy based on individual firms' bond-price reactions to intermediaries' earnings announcements. The key idea behind this strategy is that the effects of information about nonfinancial firms' conditions (e.g., their productivity or demand) should be similar for bonds with comparable characteristics issued by a single firm. Therefore, by studying within-firm variation in bond-price reactions to intermediaries' earnings announcements, one can isolate the effect of intermediaries' earnings announcements beyond those driven by information about nonfinancial firms' conditions.

We implement this empirical strategy by estimating the local projection:

$$\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \pi_{k(j)it} v_{\mathrm{F},t} + \Gamma' Z_{jt} + u_{jith}, \tag{5}$$

where $\Delta z_{k(j)it}$ represents the cumulative changes in bond k's option-adjusted spreads over h days; $v_{\mathrm{F},t}$ is the broad financial shock around intermediary i's earnings announcement; $\pi_{k(j)it}$ is the share of bond k issued by firm j held by intermediary i in the quarter preceding its earnings announcement in period t; α_{jt} is a firm-by-shock fixed effect; and Z_{jt} is a vector of bond controls that includes bond holdings $\pi_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, trailing average, month-to-date changes in spreads, and bond liquidity measured by bid-ask spreads. We estimate (5) by focusing on the subset of firms with more than 10 bonds outstanding—allowing us to exploit within-firm variation in bonds' holdings by intermediaries—and on bonds rated CCC or worse, which are most exposed to financial shocks.

Panel (d) of Figure 1 shows that within a firm, bonds with more substantial holdings by an earnings-releasing intermediary exhibit a larger sensitivity, in absolute value, to the broad financial shocks. In response to a 1% negative financial shock, spreads of bonds fully held by the earnings-releasing intermediary rise by 1 percentage point more than those of bonds with no holding by the intermediary. This result rejects the null hypothesis that the estimated reaction of nonfinancial firms' bond prices to intermediaries' earnings announcements is purely driven by information about nonfinancial firms' conditions (in which case we would expect the estimated within-firm elasticity to be not significantly different from zero). These findings are consistent with intermediaries' announcements containing information about their net worth, which, under short-term trading frictions, can lead to different prices for bonds with similar risk (see Morelli *et al.*, 2022).

4.2. Purging financial shocks from information channels

The possibility that the stock market's reactions to intermediaries' earnings announcements documented in Section 3 are influenced by information about nonfinancial firms' conditions contained in these announcements is reminiscent of the "information channel" studied in the monetary policy literature—in which estimates of the effect of monetary-policy surprises on the aggregate economy may reflect central banks' private information that is revealed in these surprises (see, for example, Nakamura and Steinsson, 2018b; Bauer and Swanson, 2023). In this section, we build on the methods developed in this literature using sign restrictions to purge monetary surprises from information channels (e.g., Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020), and propose using sign restrictions to purge financial shocks of news about nonfinancial firms' conditions contained in intermediaries' earnings announcements.

Methodology. Our approach is motivated by the predictions of models in which debt markets feature intermediaries facing financial frictions, and the intermediation premium is determined to equate the supply and demand of funds (e.g., Morelli *et al.*, 2022).[12] As illustrated in Appendix A, in this framework, positive news about intermediaries' net worth and positive news about nonfinancial firms' conditions have opposite effects on the intermediation premium associated with nonfinancial firms' borrowing costs. On the one hand, positive news about intermediaries' net worth (for example, due to a positive return on their investments) leads to an increase in their funds available to lend, which boosts the credit supply and lowers the intermediation premium. On the other hand, positive news about the future productivity or demand faced by nonfinancial firms implies an increase in the demand for credit, which leads to an increase in the intermediation premium. These observations suggest that we can purge broad financial shocks from news about nonfinancial firms' conditions using sign-restriction methods.

To implement this idea, we use data on the excess bond premium (EBP; Gilchrist *et al.*, 2021, described in more detail in Section 2), which measures nonfinancial financing costs in the absence of default risks. To match the daily frequency of the EBP, we use for the decomposition the measure of broad financial shocks that include earnings announcements outside of trading hours. Appendix Figure B.4 shows the joint distribution between event-time changes in intermediaries' stock prices and the EBP. In quadrants I and III, the comovements between stock prices and the EBP are negative, consistent with news about intermediaries' net worth. In quadrants II and IV, the comovements between stock prices and the EBP are positive, consistent with news about nonfinancial firms.

[12] In this framework, the intermediation premium is defined as the component of nonfinancial firms' spreads that would be observed if debt were risk-free.

We decompose the broad financial shocks, $\boldsymbol{v}_{\mathrm{F}}$ into two orthogonal components:

$$\boldsymbol{v}_{\mathrm{F}} = \boldsymbol{v}_{\mathrm{F,purged}} + \boldsymbol{v}_{\mathrm{F,res}}, \tag{6}$$

where $\boldsymbol{v}_{\mathrm{F,purged}}$ is the vector of "purged financial shocks," and $\boldsymbol{v}_{\mathrm{F,res}}$ is a residual component, each of length T. The sign restrictions are that $\boldsymbol{v}_{\mathrm{F,purged}}$ is negatively correlated with changes in the EBP, $\Delta\rho$, and $\boldsymbol{v}_{\mathrm{F,res}}$ is positively correlated with changes in the EBP. That is, the decomposition satisfies:

$$\begin{bmatrix} \boldsymbol{v}^{\mathrm{F}} & \Delta\boldsymbol{\rho} \end{bmatrix} = \begin{bmatrix} \boldsymbol{v}_{\mathrm{F,purged}} & \boldsymbol{v}_{\mathrm{F,res}} \end{bmatrix} \begin{bmatrix} 1 & - \\ 1 & + \end{bmatrix}, \tag{7}$$

$$\boldsymbol{v}^{'}_{\mathrm{F,purged}} \boldsymbol{v}_{\mathrm{F,res}} = 0, \tag{8}$$

$$\mathrm{var}(\boldsymbol{v}_{\mathrm{F,purged}}) + \mathrm{var}(\boldsymbol{v}_{\mathrm{F,res}}) = \mathrm{var}(\boldsymbol{v}_{\mathrm{F}}). \tag{9}$$

We perform the decomposition using Givens rotation matrices, closely following the algorithm developed by Jarocinski (2020). In addition, we alternatively perform the decomposition using a simple "poor man's sign restrictions" proposed by Jarociński and Karadi (2020). Among the set of admissible structural shocks that satisfy the sign restrictions, we use median shocks as $\boldsymbol{v}_{\mathrm{F,purged}}$ and $\boldsymbol{v}_{\mathrm{F,res}}$. Appendix E provides further details on the procedures.

Results. Using the purged financial shocks, we estimate an event-study framework similar to those considered in Section 3.2:

$$\Delta y_t = \alpha + \beta v_{\mathrm{F}t,\mathrm{purged}} + u_t, \tag{10}$$

where Δy_t is the log daily change of the S&P 500 Ex-Financials index. The identifying assumption to interpret the estimated coefficient β as causal is that, around intermediaries' earnings announcements, the purged financial shocks are driven by the information about intermediaries' net worth contained in the announcements and not by other factors that affect the stock price of nonfinancial firms.

Table 4 shows that using purged financial shocks leads to an estimated elasticity of

Table 4: Stock Market's Reaction to Purged Financial Shocks

	(1)		(2)	(3)	(4)
	Sign restrictions		**Event-Time**		**Heteroskedasticity**
$v_{\text{F,purged}}$	1.276***	v_{F}	0.624**		
	(0.306)		(0.195)		
		Δp_{F}		0.477***	0.434***
				(0.086)	(0.022)
					[0.384,0.483]
R^2	0.068		0.024	0.093	-
N	492		635	635	4,749

Notes: This table reports stock market's reaction to intermediaries' earnings announcements at daily frequency. Column 1 estimates: $\Delta y_t = \alpha + \beta v_{\text{F}t,\text{purged}} + u_t$, where Δy_t is the log daily change of the S&P 500 Ex-Financials index; and $v_{\text{F}t,\text{purged}}$ is the purged financial shock decomposed using sign restrictions specified in (7)–(9) in the main text. The sample for this analysis starts in July 2002 when the excess bond premium data becomes available. Columns 2 estimates the baseline event-study regression at daily frequency: $\Delta y_t = \alpha + \beta v_{\text{F}t} + u_t$, where Δy_t is the daily log change of the S&P 500 Ex-Financials index; and $v_{\text{F}t}$ is the broad high-frequency financial shock aggregated to daily frequency. Column 3 estimates a variant of Column 2, where the independent variable is $\Delta p_{\text{F}t}$ (defined in Table 3) aggregated to the daily frequency. Column 4 reports the heteroskedasticity-based estimator for γ from the bivariate model consisting of $\Delta p_{\text{F}t}$ and the log daily change of the S&P 500 Ex-Financials index. The F-statistic from the first stage is 147. Standard errors and 95% confidence intervals are computed with stratified bootstrap, as described in the text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

nonfinancial firms' stock prices to the releasing intermediary's stock prices that is twice as large as when using broad financial shocks.[13] This result implies that information about intermediaries' net worth revealed during these announcements has a significant effect on the stock prices of nonfinancial firms. Appendix Table B.7 shows that we obtain similar results if we purge financial shocks using the "poor man's sign restrictions" instead of Givens rotation matrices. Finally, Appendix Table B.7 shows that the residual component of the financial shock, $\boldsymbol{v}_{\text{F,res}}$, has a smaller and not statistically significant association with nonfinancial firms' stock prices. This suggests that the information about nonfinancial firms revealed

[13]The estimates from the event-study framework using broad financial shocks presented in Table 4 are larger than those reported in Table 3 because the former are estimated at a daily frequency (which is the frequency at which purged financial shocks are constructed, given the availability of the EBP), while the latter are estimated in a narrow window (60 minutes) around intermediaries' earnings announcements. Columns (3) and (4) show that we obtain a similar daily-frequency estimated elasticity from the heteroskedasticity-based framework as in the event-study framework using a comparable regressor (Δp_{F}), indicating that the elasticity estimates from the event-study framework are not driven by unobserved common shocks, unrelated to the release of intermediaries' earnings, that affect both nonfinancial firms' outcomes and financial intermediaries' stock prices on a daily basis around earnings announcements.

during intermediaries' earnings announcements may not be sufficiently strong to dominate the link between $\boldsymbol{v}_{\mathrm{F,res}}$ and nonfinancial firms' stock prices around intermediaries' earnings announcements.[14]

5. Evidence on Transmission Mechanisms and Macroeconomic Effects

This section studies how financial shocks transmit to the rest of the economy. Section 5.1 documents that the effects of financial shocks exhibit aggregate state dependency. Section 5.2 studies the role of firms' financial positions by examining their heterogeneous responses to financial shocks. Finally, Section 5.3 analyzes how these shocks impact macroeconomic variables.

5.1. Aggregate state dependency

Empirical evidence on the role of financial intermediaries in the macroeconomy often comes from analyzing episodes of financial crises (Reinhart and Rogoff, 2009; Chodorow-Reich, 2014; Huber, 2018). Motivated by this evidence, we investigate the importance of aggregate conditions in the transmission of financial shocks by estimating:

$$\Delta y_{jt} = \alpha_j + \beta_h \cdot v_{\mathrm{F},t} \mathbb{1}(N_t > \bar{N}_t) + \beta_l \cdot v_{\mathrm{F},t} \mathbb{1}(N_t < \bar{N}_t) + \Gamma' Z_t + u_{jt}, \tag{11}$$

where N_t is the total equity of U.S.-chartered depository institutions, obtained from the Enhanced Financial Accounts reported by the Federal Reserve; $\mathbb{1}(N_t > \bar{N}_t)$ is an indicator variable which takes the value 1 if the total equity is above its HP-filtered trend $\bar{N}_t$ and 0 otherwise; and Z_t is a vector of macro controls (including output, payrolls, a recession indicator, and their interaction with broad financial shocks). The coefficients of interest, β_h and β_l, measure the elasticity of nonfinancial firms' stock price to financial shocks varies when the financial system has high and low capitalization, respectively.

[14] To interpret this result, it is worth noting that other channels could be captured in $\boldsymbol{v}_{\mathrm{F,res}}$, aside from information about nonfinancial firms. For instance, increases in the stock price of a releasing intermediary might reflect negative conditions for competing intermediaries outside of our sample, which could be associated with an increase in the EBP and potentially a decline in nonfinancial firms' stock prices.

Table 5: State Dependency of Stock Market's Reaction to Intermediaries' Earnings Announcements

	(1)	(2)	(3)
	S&P500 constituents		
Average (v_{F})	0.245^{**}		
	(0.104)		
High capitalization		0.055	0.017
		(0.107)	(0.113)
Low capitalization		0.311^{**}	0.269^{**}
		(0.130)	(0.105)
Adjusted R^2	0.008	0.008	0.011
Observations	173,475	173,475	173,475
Macro interactions	no	no	yes
Security fixed effects	yes	yes	yes
Double clustering	yes	yes	yes

Notes: This table reports results from estimating (11): $\Delta y_{jt} = \alpha_j + \beta_h \cdot v_{\mathrm{F},t}\mathbb{1}(N_t > \bar{N}_t) + \beta_l \cdot v_{\mathrm{F},t}\mathbb{1}(N_t < \bar{N}_t) + \Gamma' Z_t + u_{jt}$, where Δy_{jt} is the 60-minute log price change of non-financial constituent securities of the S&P 500 index, $v_{\mathrm{F},t}$ is the broad financial shock; N_t is the total equity of U.S.-chartered depository institutions; and Z_t is a vector of macro controls (including output, payrolls, a recession indicator, and their interaction with broad financial shocks). Standard errors are two-way clustered at shock and security levels and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 5 shows that the elasticity of nonfinancial firms' stock prices to financial shocks is larger when the financial system is undercapitalized. When the financial system is well-capitalized, the elasticity is economically small and statistically insignificant. Appendix Table D.6 shows a similar state dependency with the purged financial shocks. This state dependency suggests that the overall condition of the financial system is a key factor in the aggregate effects of intermediaries on the economy (as emphasized, for example, by Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014).

5.2. Firm heterogeneity

We also provide evidence that nonfinancial firms' financial positions play an important role in our results, by estimating the model:

$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta v_{\mathrm{F},t} + \gamma v_{\mathrm{F},t} x_{jt-1} + \Gamma' Z_{jt-1} + u_{jt}, \tag{12}$$

Table 6: Firm Heterogeneity in Stock Market's Reaction to Intermediaries' Earnings Announcements

	Average	Leverage (High)	Credit Ratings (Invt Grade)	Liquidity (Liquid)
$v_{\mathrm{F},t}$	0.247***	0.240***	0.362***	0.250***
	(0.079)	(0.090)	(0.133)	(0.087)
$v_{\mathrm{F},t} \times x_{jt-1}$		0.015	-0.088**	-0.006
		(0.014)	(0.043)	(0.015)
Adjusted R^2	0.025	0.025	0.040	0.025
Observations	750,260	750,260	162,281	750,241
Firm controls	no	yes	yes	yes
Firm FE	yes	yes	yes	yes
Quarter-sector FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

Notes: This table reports results from estimating (12): $\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta v_{\mathrm{F},t} + \gamma v_{\mathrm{F},t} x_{jt-1} + \Gamma' Z_{jt-1} + u_{jt}$, where Δy_{jt} is the 60-minute log price change of non-financial constituent securities of the S&P 500 index, $v_{\mathrm{F},t}$ is the broad financial shock, and x_{jt} is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity. Leverage is defined as the sum of debt in current liabilities and long-term debt over the sum of total assets and market valuation minus common equity; investment-grade credit rating is defined as ratings between AAA and BBB- by Standard & Poor's; and liquidity is defined as the sum of cash and short-term investment over total assets; Z_{jt-1} is a vector of firm controls, including firm characteristic x_{jt-1}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. Standard errors are two-way clustered at shock and security levels and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

where the dependent variable, Δy_{jt}—as in previous sections—is the log change in nonfinancial firms' stock prices in the 60-minute window around a financial shock; x_{jt-1} is an indicator variable that equals 1 for firms with high leverage, investment-grade credit rating, or high liquidity; α_j is a firm fixed effect; α_{sq} is a sector-by-quarter fixed effect; and Z_{jt-1} is a vector of firm controls, including firm characteristic x_{jt-1}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. We interact financial shocks with the indicator variable x_{jt-1} to capture a firm's financial position. The coefficient of interest, γ, measures how the elasticity of nonfinancial firms' stock price to financial shocks depends to firms' financial positions.[15] Standard errors are two-way clustered by firm and shock.

Table 6 shows that firms' financial positions affect the elasticity of nonfinancial firms'

[15] A similar strategy has been used in the literature analyzing the heterogeneous effects of monetary policy shocks on nonfinancial firms (Ottonello and Winberry, 2020; Anderson and Cesa-Bianchi, 2020; Jeenas, 2019). For this analysis, we expand the sample from S&P 500 nonfinancial constituents to all publicly traded nonfinancial firms in the U.S., which is matched with Compustat firm characteristics.

stock price to financial shocks. Appendix Table D.7 repeat the estimation with the purged financial shock and find a consistent pattern. Credit risk is an important source of heterogeneity for the transmission of financial shocks: Firms with lower credit ratings are those whose stock prices feature a larger elasticity to financial shocks. We interpret this evidence as suggesting that firms' financial positions (and potentially financial heterogeneity) matter in the transmission of financial shocks.

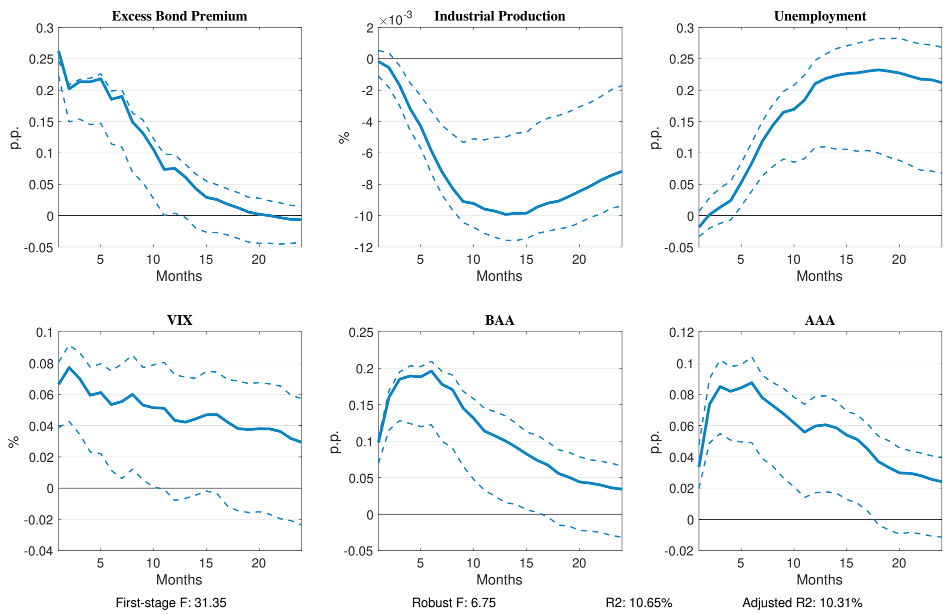
To compare the transmission of monetary and financial shocks, Appendix Table B.6 reports the heterogeneous responses of firms in our sample for high-frequency monetary policy shocks, constructed as in Gorodnichenko and Weber (2016). Consistent with previous studies (e.g., Ottonello and Winberry, 2020), firms with higher credit ratings are more responsive to monetary policy, which suggests that firms' default risks play an important role in the transmission of both monetary and financial shocks.

5.3. Macroeconomic Effects

Finally, we study the effects of financial shocks on macroeconomic variables. For this analysis, we turn to longer horizons at monthly frequency instead of the high frequency our analysis has so far focused on. Our econometric model is an external-instrument vector autoregression (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015) that consists of the excess bond premium (EBP), log industrial production, unemployment rate, log VIX index, and the spreads between AAA- and BAA-rated bonds and 10-year treasury yields. Using high-frequency financial shocks as the external instrument for the EBP, we identify the effects of financial shocks on macroeconomic outcomes through affecting credit supply and nonfinancial firms' financing costs. The identifying assumption is that high-frequency financial shocks are correlated with structural shocks to the EBP but uncorrelated with other structural shocks. The sample for this analysis starts in January 1973, when the EBP data became available, and ends in January 2020, before the onset of the Covid pandemic. We aggregate purged financial shocks to monthly frequency to match the remaining macro series.[16]

[16] This analysis uses the purged financial shock, since it isolates the component of the broad financial shock that reflects changes in credit supply (see Section 4.2 for details) and is more likely to serve as a valid instrument for nonfinancial firms' borrowing costs. Appendix Figure D.2 re-estimates the VAR using broad financial shocks and finds a similar pattern in impulse responses, but with a lower F-statistic in the first stage.

Figure 2: The Macroeconomic Effects of Financial Shocks



Notes: This figure reports the impulse responses to a one-standard-deviation financial shock to the supply of credit estimated in an external-instrument VAR. The VAR consists of the excess bond premium, log industrial production, unemployment rate, log VIX index, and the spreads between AAA- and BAA-rated bonds and 10-year treasury yields, with the excess bond premium instrumented by high-frequency purged financial shocks. Dashed lines represent 90% bootstrapped confidence intervals.

Figure 2 presents the impulse responses to a one-standard-deviation financial shock. The first panel shows that the EBP rises on impact by 26 basis points, and thus represents an increase in firms' borrowing costs. The F-statistic from the first stage is 31, which is above the threshold suggested by Stock, Wright and Yogo (2002) to rule out possible weak instruments. Financial shocks have significant effects on long-run macroeconomic outcomes. The next panels show that industrial production declines and remains depressed by 1 basis point for over a year; long-run unemployment rises and shows little sign of recovery; macro uncertainty remains elevated at around 5 basis points for a year; and firms face higher borrowing costs in bond markets, with a bigger effect on riskier firms.

In Appendix Figure D.3, we compare the impulse responses identified using external instrument with those identified using Cholesky decomposition. The ordering of the Cholesky assumes that shocks to the EBP affect macroeconomic conditions with a lag, but can affect financial variables contemporaneously. At monthly frequency, however, macroeconomic conditions may respond to the EBP and the EBP may to respond to financial variables. Addressing the potential simultaneity using high-frequency financial shocks as the external instrument, we obtain impulse responses that are more conservative and precisely estimated compared to those identified through the Cholesky decomposition.

6. Conclusions

In this paper, we propose a new measure of financial shocks based on high-frequency changes in the stock price of large financial intermediaries' around their earnings announcements. Then, to study the effects of financial shocks on the aggregate economy, we exploit the granularity of financial shocks that stem from the considerable size of U.S. publicly traded financial intermediaries. We document intermediaries' substantial effects on the stock price and borrowing costs of nonfinancial firms. The effects are stronger for firms with high default risk and when the financial system is undercapitalized. In addition, financial shocks have large and persistent effects on the macroeconomy.

The high-frequency financial shocks developed in the paper can be used directly by researchers conducting empirical research on macroeconomics, similar to the large body of evidence developed using high-frequency monetary policy shocks. Our empirical findings on the effect of intermediaries on the aggregate economy can also be useful when combined with models aimed at understanding the role of financial intermediaries in determining the aggregate transmission of shocks. We leave the combination of models with these empirical estimates for future research.

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Online Appendix

A. An Illustrative Theoretical Framework

In this section, we consider a model to motivate and interpret our empirical analysis.

A.1. Environment

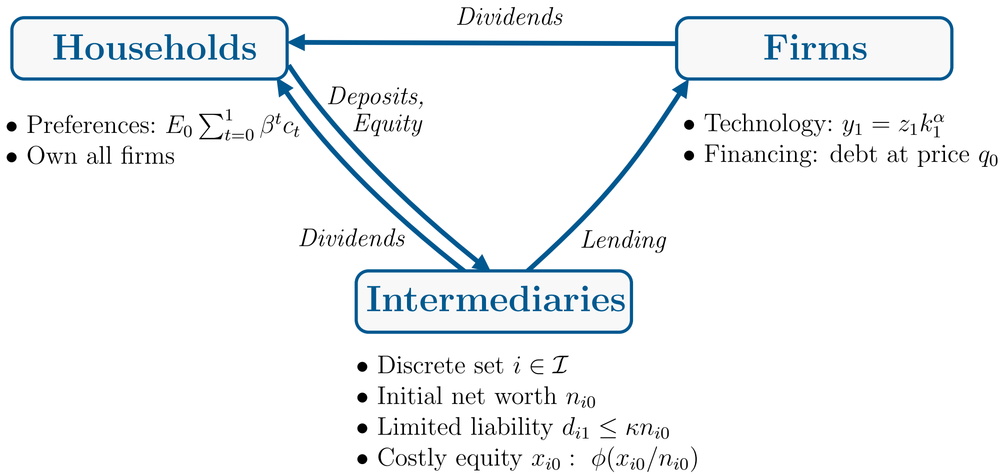
There are two periods: $t = 0, 1$; and two goods: final and capital goods. The economy is populated by a unit mass of identical households and nonfinancial firms and a discrete set of intermediaries indexed by $i \in \mathcal{I}$. Figure A.1 summarizes the model economy.

Households have preferences over consumption given by $c_0 + \beta \mathbb{E}_0 c_1$, where c_t is the consumption of final goods in period t and $\beta \in (0, 1)$ is a subjective discount factor. Households start with an initial endowment of final goods of y_0.

Nonfinancial firms have access to a technology for producing final goods in period 1 using capital input: $y_1 = z_1 k_1^{\alpha}$, where z_1 is an aggregate productivity shock with bounded support; and a linear technology to accumulate capital goods from the final good. Capital fully depreciates after production. Firms cannot raise equity and must finance their investment by borrowing from financial intermediaries in competitive markets at the price q_0.

Financial intermediaries are firms owned by households that engage in financial intermediation, raising funds from households and lending to nonfinancial firms. They have an initial endowment of final goods, or net worth, n_{i0}, and can raise external finance from households in the form of deposits, d_{i1}, and equity, x_{i0}, both subject to frictions, modeled following the literature on frictional financial intermediaries (e.g., Gertler and Kiyotaki, 2010; Morelli *et al.*, 2022). On the deposit side, intermediaries face limited liability constraints, linking their deposits to their net worth: $d_{i1} \leq \kappa n_{i0}$, with $\kappa \geq 0$. On the equity side, intermediaries face a cost to raise equity $\phi\left(\frac{x_{i0}}{n_{i0}}\right)$. As in the quantitative corporate finance literature (e.g., Gomes, 2001; Hennessy and Whited, 2007), these costs capture flotation costs, adverse selection premiums, and other external financing costs. The parameter $\phi \geq 0$ governs the degree of frictions intermediaries face when raising external finance and is a key parameter in our analysis. The case of $\phi = 0$ corresponds to a frictionless economy, where households directly lend to nonfinancial firms.

Figure A.1: Model Economy



A.2. Optimization

Households. In period 0, after receiving their initial endowment and the net transfers from their initial ownership of nonfinancial firms and intermediaries, households choose their investments in financial securities: deposits on financial intermediaries, d_{i1}, and shares of nonfinancial firms and intermediaries, a_{f1} and a_{i1}. Households' problem is then given by

$$\begin{aligned} \max_{d_{i1}, a_{f1}, a_{i1}} \quad & c_0 + \beta \mathbb{E}_0 c_1 && (13) \\ \text{s.t.} \quad & c_0 + p_{f0} a_{f1} + \sum_{i \in \mathcal{I}} p_{i0} a_{i1} + \sum_{i \in \mathcal{I}} d_{i1} = y_0 + \pi_{f0} + p_{f0} + \sum_{i \in \mathcal{I}} (\pi_{i0} + p_{i0}), \\ & c_1 = \pi_{f1} a_{f1} + \sum_{i \in \mathcal{I}} a_{i1} \pi_{i1} + \sum_{i \in \mathcal{I}} R_d d_{i1}, \end{aligned}$$

where households' initial shares of nonfinancial firms and financial intermediaries have been normalized to one; π_{ft} and π_{it} denote the net transfers from nonfinancial firms and intermediary i to households in period t; p_{f0} and p_{i0} denote the price of shares of nonfinancial firms and financial intermediary i in period 0; and R_d denotes the gross interest rate on deposits. Households' optimal choice of financial securities implies that

$$R_d = \frac{1}{\beta}, \qquad p_{f0} = \beta \mathbb{E}_0 \pi_{f1}, \qquad p_{i0} = \beta \mathbb{E}_0 \pi_{i1}, \tag{14}$$

which determine the equilibrium deposit rate and share prices.

Nonfinancial firms. In period 0, nonfinancial firms choose the capital to produce in the following period, k_1. Their problem is given by

$$\begin{aligned}
\max_{k_1 \geq 0, b_1, \pi_{f0} \geq 0} \; & \pi_{f0} + \beta \mathbb{E}_0 \pi_{f1} \\
\text{s.t. } \pi_{f0} = \; & q_0 b_1 - k_1, \\
\pi_{f1} = \; & z_1 k_1^{\alpha} - b_1,
\end{aligned} \tag{15}$$

where b_1 denotes nonfinancial firms' borrowing from financial intermediaries at the price q_0. Nonfinancial firms' choice of capital is characterized by the Euler equation

$$\frac{1}{q_0} = \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1}, \tag{16}$$

which equates the marginal cost of capital—given by the interest rate on borrowing $\frac{1}{q_0}$, because borrowing is the marginal source of financing—to its expected marginal benefit (because of the assumed properties for the production technology, the nonnegative dividend constraint is always binding).

Financial intermediaries. Given its initial net worth n_{i0}, the problem of financial intermediary i is given by

$$\begin{aligned}
\max_{x_{i0}, b_{i1}} \; & \pi_{i0} + \beta \pi_{i1} \\
\text{s.t. } \pi_{i0} = \; & -x_{i0} \left(1 + \mathbb{1}_{\{x_{i0} > 0\}} \phi \left(\frac{x_{i0}}{n_{i0}} \right) \right), \\
\pi_{i1} = \; & b_{i1} - R_d d_{i1}, \\
q_0 b_{i1} = \; & n_{i0} + x_{i0} + d_{i1}, \\
d_{i1} \leq \; & \kappa n_{i0},
\end{aligned} \tag{17}$$

where b_{i1} is the lending by intermediary i to nonfinancial firms. Intermediaries' problem has no uncertainty because, for simplicity, debt is assumed to be risk free. In an interior solution with $x_{i0} > 0$, intermediaries' optimal allocation is characterized by

$$1 + 2\phi \left(\frac{x_{i0}}{n_{i0}} \right) = \beta R_d + \mu_i \tag{18}$$

$$\beta R_d + \mu_i = \beta \frac{1}{q_0}, \tag{19}$$

with complementary slackness condition

$$(d_{i1} - \kappa n_{i0})\mu_i = 0, \tag{20}$$

where μ_i denotes the Lagrange multiplier associated with the limited liability constraint of intermediary i. Equation (18) implies that intermediaries equate the marginal costs of the two sources of financing: the marginal cost of raising equity with the shadow marginal cost of deposits. In addition, Equation (19) implies that intermediaries equate the marginal cost of external finance with the return on lending. Note that (18) and (19) imply that when the rate on lending exceeds the deposit rate ($\frac{1}{q_0} > R_d$), limited liability constraints bind ($\mu_i > 0$ for all i) and all intermediaries raise the same external finance relative to their net worth $\chi_0 \equiv \frac{x_{i0}}{n_{i0}}$.

A.3. Equilibrium

The equilibrium in this economy is then defined as follows:

***Definition* 1.** *Given intermediaries' initial net worth* $(n_{i0})_{i\in\mathcal{I}}$ *and nonfinancial firms' productivity process* $\{z_1\}$*, an equilibrium is a set of state-contingent households' allocations* $\{c_0, c_1, d_1, a_{f1}, (a_{i1})_{i\in\mathcal{I}}\}$*; nonfinancial firms' allocations* $\{\pi_{f0}, \pi_{f1}, b_1, k_1\}$*; financial intermediaries' allocations* $(\pi_{i0}, \pi_{i1}, d_{i0}, x_{i0}, b_{i1})_{i\in\mathcal{I}}$*; and prices* $\{q_0, p_{f0}, (p_{i0})_{i\in\mathcal{I}}\}$ *such that*

i. Given prices, households' allocations solve (13)*; nonfinancial firms' allocations solve* (15)*; and financial intermediaries' allocations solve* (17)*.*

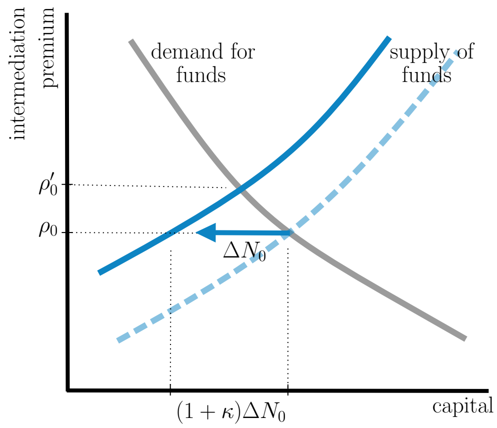
ii. Asset markets clear—i.e., $b_1 = \sum_{i\in\mathcal{I}} b_{i1}$*,* $d_1 = \sum_{i\in\mathcal{I}} d_{i1}$*,* $a_{f1} = 1$*, and* $a_{i1} = 1$ *for all* i*.*

We represent the equilibrium of the model using a demand–supply-of-funds scheme (similar to that developed by Morelli *et al.*, 2022). On the side of intermediaries, we focus on the equilibrium in which their limited liability constraints bind. By integrating intermediaries' flow-of-funds constraints and imposing market clearing for the debt market, we obtain a relationship between capital, k_1, and the intermediation premium, $\rho_0 \equiv \beta\frac{1}{q_0}$, that we label the *aggregate supply of funds*:

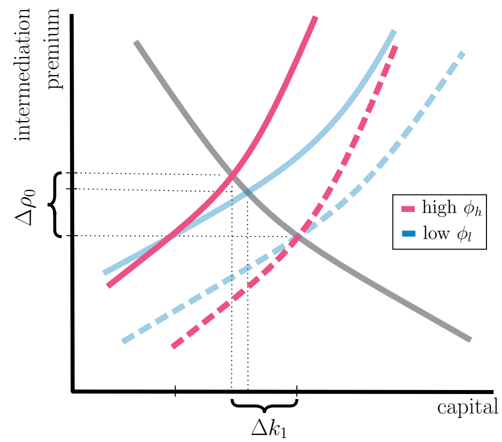
$$\mathcal{K}^s(\rho_0, N_0, \phi) = N_0(1 + \kappa + \mathcal{X}(\rho_0, \phi)), \tag{21}$$

where $\mathcal{K}^s(\rho_0, N_0, \phi) = q_0 \sum_{i\in\mathcal{I}} b_{i0}$; $N_0 = \sum_{i\in\mathcal{I}} n_{i0}$ denotes aggregate net worth; and $\mathcal{X}(\rho_0, \phi) = \frac{1}{2\phi}(\rho_0 - 1)$. The relationship between the supply of funds and the intermediation premium is

Figure A.2: The Aggregate Effects of Financial Shocks and the Degree of Intermediaries' Financial Frictions



(a) The Aggregate Effects of Financial Shocks



(b) The Role of Intermediaries' Frictions

upward sloping for $\phi > 0$ (i.e., $\frac{\partial \mathcal{K}^s(q_0, N_0, \phi)}{\partial \rho_0} > 0$) because in this case, intermediaries face an upward-sloping cost to raise external finance (governed by ϕ), which implies that to supply more funds, the returns on lending must be larger. On the side of firms, the Euler equation for capital implies a relationship between capital and interest rates, which we label the *aggregate demand for funds*: $\mathcal{K}^d(\rho_0) = (\frac{\alpha\beta}{\rho_0}\mathbb{E}_0 z_1)^{\frac{1}{1-\alpha}}$. For a given discount rate, the relationship between the demand for funds and the intermediation premium is downward sloping (i.e., $\frac{\partial \mathcal{K}^d(q_0)}{\partial \rho_0} < 0$), reflecting the fact that lower borrowing costs reduce the marginal cost of capital, leading to higher investment by firms. Figure A.2a depicts the equilibrium capital and intermediation premium as the intersection between the aggregate supply of and demand for funds.

A.4. The effects of idiosyncratic changes in intermediaries' net worth

Model experiment. Consider now an unexpected change in the initial idiosyncratic net worth of some intermediary $\iota \in \mathcal{I}$. Since each intermediary has a mass of net worth, the change in some intermediary's net worth leads to a change in the initial aggregate net worth (i.e., $\frac{\partial N_0}{\partial n_{\iota 0}} > 0$); this is the assumption we refer to in the empirical analysis as "granularity." Given that the model features aggregation across intermediaries, we can analyze the effect of this idiosyncratic shock by analyzing the effect of a change in the aggregate net worth N_0.

Panel (a) of Figure A.2 represents the effect of a contraction in the initial aggregate net worth N_0 in the equilibrium investment and intermediation premium. This shock implies that financial intermediaries have fewer internal resources to lend, which reduces the aggregate supply of funds for a given level of the intermediation premium and increases the equilibrium intermediation premium. Panel (b) shows that the aggregate effects of the shock on investment and the intermediation premium depend on intermediaries' degree of financial frictions, measured by the marginal cost of external finance ϕ. Economies in which intermediaries have a higher marginal cost of external finance ϕ have a steeper aggregate supply of funds curve because intermediaries require a larger increase in the intermediation premium in order to issue external finance to finance lending to nonfinancial firms. Changes in the initial aggregate net worth have a larger impact on investment because financial intermediaries require higher increases in the intermediation premium to be willing to recapitalize by raising external finance. In economies with a smaller ϕ, intermediaries face a flatter marginal cost curve of external finance; changes in the initial net worth of intermediaries have a smaller impact on investment because intermediaries can more easily recapitalize, and they require a smaller increase in the intermediation premium to be willing to recapitalize and increase lending. In the extreme case in which intermediaries face no cost of external finance, the aggregate supply of funds becomes perfectly elastic, and changes in the initial net worth of intermediaries have no effects on investment. The following proposition formalizes this result.

***Proposition* 1.** *If $\phi = 0$, then $\frac{\partial k_1}{\partial N_0} = 0$. If $\phi > 0$ and for large enough z_1 such that intermediaries' limited liability constraints bind (i.e., $\mu_i > 0$ for all i), then $\frac{\partial k_1}{\partial N_0} > 0$ with $\partial \frac{\partial k_1}{\partial N_0} / \partial \phi > 0$ for $\phi \to 0$.*

Proof. See Section A.6. □

This discussion suggests that analyzing the macroeconomic effects of idiosyncratic changes in intermediaries' net worth—as we do in our empirical analysis—is highly informative regarding the degree of financial frictions faced by intermediaries. We next discuss in more detail the link between the model experiment and the empirical analysis.

Link to empirical analysis. Our empirical analysis measures financial shocks as the stock price changes of releasing intermediaries around their earnings announcements. In our model, combining (14) with intermediaries' flow-of-funds constraints under binding limited liability, the price of intermediary shares is given by $p_{i0} = n_{i0} \left(\frac{1+\chi_0+\kappa}{\rho_0} - \kappa \right)$. Therefore, if intermediaries' earnings releases provide information about n_{i0}, we expect our empirical measures of financial shocks to capture these changes in net worth (both directly and through their effect on the intermediation premium ρ_0).

The empirical analysis studies the relationship between financial shocks and nonfinancial firms' stock prices and borrowing costs. In our model, using (14) and nonfinancial firms' flow-of-funds constraint, the stock price of nonfinancial firms is given by $p_{f0} = \beta(\mathbb{E}_0 z_1 k_1^\alpha - b_1) = \beta(1-\alpha)\mathbb{E}_0 z_1 k_1^\alpha$. Therefore, if intermediaries' earnings releases provide information about n_{i0}, we expect changes in nonfinancial firms' stock prices to reflect the changes in firm investment characterized in Proposition 1. In addition, we expect the excess bond premium to reflect the changes in the intermediation premium, ρ_0, discussed in the previous section.

In our model, changes in individual intermediaries' net worth affect aggregate net worth (i.e., $\frac{\partial N_0}{\partial n_{\iota 0}} > 0$). For this reason, our empirical analysis focuses on large intermediaries, which are more likely to satisfy this condition. A key difference between the empirical setting and the model is that, in the former, releasing intermediaries know their net worth before the earnings announcement, while in the latter, all agents learn about unexpected net worth changes simultaneously. Although we expect the economic forces discussed in this section to be present in a model with differing information sets that resemble those in the empirical setting, accounting for these differences may be important when mapping the empirical estimates to a quantitative setting.

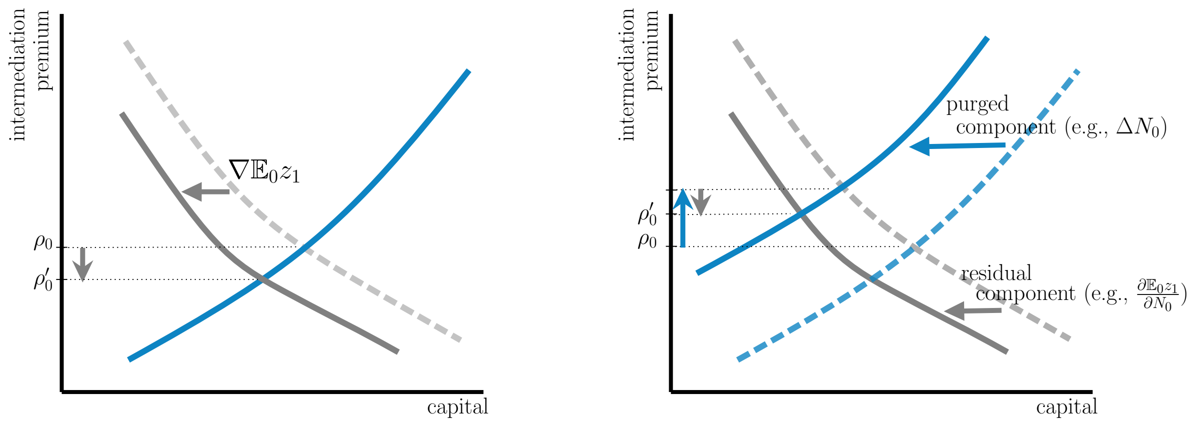
A.5. Additional Information Contained in Intermediaries' Earnings Releases

We now extend the model to discuss how, as outlined in Section 3, asset price reactions to intermediaries' earnings announcements may reflect not only information about the releasing intermediary's net worth but also conditions in the broader financial sector or nonfinancial firms. This discussion motivates our method for purging financial shocks using sign restrictions, as detailed in Section 4.2.

Information about the financial sector. An individual intermediary's earnings announcement can naturally contain information about non-releasing financial intermediaries. For instance, it may reveal information about the net worth of other intermediaries, the cost of raising external finance (e.g., an increase in the parameter ϕ), or, in a version of our model where lending is risky, about investors' risk aversion. Through the lens of our model, unexpected changes in these variables would shift or alter the slope of credit supply, $\mathcal{K}^s(\rho_0, N_0, \phi)$.

For these effects to drive the positive elasticity between nonfinancial firms' stock prices and releasing financial intermediaries' stock prices documented in Section 3.2, it would require that an unexpected contraction in intermediaries' stock prices provides information about non-releasing intermediaries, which contracts credit supply, raises the intermediation premium, and reduces nonfinancial firms' investment. However, our empirical results in Section 3.1 on the limited comovement between the stock prices of releasing and non-releasing intermediaries suggest that these information channels may be limited for non-releasing intermediaries in our sample.

Figure A.3: The Effects of Financial Shocks and Information Regarding Nonfinancial Firms' Conditions



(a) The Effect of Information Regarding Nonfinancial Firms' Conditions

(b) The Effects of Purged and Residual Components of Financial Shocks

Information about nonfinancial firms' conditions. An individual intermediary's earnings announcement can also contain information about the conditions of nonfinancial firms. In our model, the stock price of nonfinancial firms is given by $p_{f0} = \beta(1-\alpha)\left(\frac{\beta}{\rho_0}\alpha\right)^{\frac{\alpha}{1-\alpha}}(\mathbb{E}_0 z_1)^{\frac{1}{1-\alpha}}$. Therefore, even in the absence of changes in the intermediation premium induced by changes in the releasing intermediary's net worth, changes in expected productivity $\mathbb{E}_0 z_1$ released during these earnings would lead to nonfinancial firms' stock price reactions. For these effects to drive the positive elasticity between nonfinancial firms' stock prices and releasing financial intermediaries' stock prices, an unexpected contraction in intermediaries' net worth would have to signal lower future nonfinancial firms' productivity, i.e., $\frac{\partial \mathbb{E}_0 z_1}{\partial n_{\iota 0}} \geq 0$.

To identify the component of nonfinancial firms' stock price reaction driven by these information effects, our key observation is that, in our model, news about the nonfinancial firm's productivity and intermediaries' net worth have opposite effects on the intermediation premium. On the one hand, negative news about intermediaries' net worth (e.g., due to a negative return on their investments) reduces credit supply and raises the intermediation premium, as shown in Figure A.2. On the other hand, negative news about future productivity lowers credit demand and reduces the intermediation premium, as shown in Panel (a) of Figure A.3. These observations suggest that we can purge broad financial shocks of news about nonfinancial firms' conditions using sign-restriction methods, as we do in Section 4.2.

Panel (b) of Figure A.3 illustrates the sign restrictions, showing in blue the effect of the component of financial shocks purged of information channels, and in grey, that of the residual component. Contractions in both components lead to declines in financial intermediaries' stock prices. However, the two components have opposite effects on the intermediation premium: a contraction in the purged component, which incorporates the intermediaries' net worth channel, raises the intermediation premium, whereas a contraction in the residual component, which incorporates the information about nonfinancial firms' conditions (corrected for the intermediaries' net worth channel), reduces the intermediation premium. Therefore, we impose the sign restrictions so that the purged component of broad financial shocks leads to negative comovements between intermediaries' stock prices and the intermediation premium, whereas the residual component leads to positive comovements between the two.

A.6. Proofs

Proof of Proposition 1.

Proof. First, if $\phi = 0$, then intermediaries' optimality conditions (18) and (19) imply that $q_0 = \beta$. Nonfinancial firms' optimality condition (16) implies that $1 = \beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1}$, meaning that $\frac{\partial k_1}{\partial N_0} = 0$.

For $\phi > 0$, conjecture that for large enough $\mathbb{E}_0 z_1$, intermediaries' limited liability constraints bind ($\mu_i > 0$ for all i). From (18), in such equilibria, all intermediaries raise the same external finance relative to their net worth $\chi_0 \equiv \frac{x_{i0}}{n_{i0}}$. Combining (16) and (21), we obtain an implicit function that determines equilibrium capital as a function of aggregate net worth $\mathcal{K}(k_1, N_0, \phi) = 0$, with

$$\mathcal{K}(k_1, N_0, \phi) = k_1 - N_0(1 + \kappa + \frac{1}{2\phi}\left(\beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1} - 1\right)). \tag{22}$$

Note that $\frac{\partial \mathcal{K}(k_1,N_0,\phi)}{\partial k_1} = 1 - N_0 \frac{1}{2\phi} \beta \mathbb{E}_0 z_1 \alpha(\alpha - 1) k_1^{\alpha-2} > 0$; and that $\frac{\partial \mathcal{K}(k_1,N_0,\phi)}{\partial N_0} = -(1 + \kappa + \frac{1}{2\phi}\left(\beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1} - 1\right))$, which, for an equilibrium around which financial intermediaries raise equity, is negative. By the implicit function theorem, it follows that $\frac{\partial k_1}{\partial N_0} > 0$, as stated in the proposition. Using these expressions, it follows that $sign(\partial \frac{\partial k_1}{\partial N_0} / \partial \phi) = sign(N_0 \frac{1}{2} \beta \mathbb{E}_0 z_1 \alpha (1 - \alpha) k_1^{\alpha-2} - \phi \chi_0)$, which is positive for $\phi \to 0$.

Finally, we verify the conjecture that for large enough $\mathbb{E}_0 z_1$, intermediaries' limited liability constraints bind. We do so by contradiction. Assume that, contrary to our conjecture, intermediaries' limited liability constraints do not bind for any $\mathbb{E}_0 z_1$. In such equilibrium, by (18), intermediaries do not raise external finance (i.e., $x_{i0} = 0$ for all i); and by (19), $q_0 = \beta$. Given N_0, let $k_1^* = N_0(1 + \kappa)$ be the maximum level of capital that satisfies the limited liability constraint without external equity. Let z_1^* denote the level of expected productivity that satisfies nonfinancial firms' Euler equation (16) $\frac{1}{\beta} = z_1^* \alpha (k_1^*)^{\alpha-1}$. Consider now some level of expected productivity $\hat{z}_1 > z_1^*$. Let $\hat{k}_1$ denote the level of capital that satisfies nonfinancial firms' Euler equation (16) $\frac{1}{\beta} = \hat{z}_1 \alpha (\hat{k}_1)^{\alpha-1}$. Since $\hat{k}_1 > k_1^*$, it follows that $\hat{k}_1 > N_0(1+\kappa)$, which contradicts the assumption that the limited liability constraint does not bind. □

B. Additional Tables and Figures

Table B.1: Descriptive Statistics for Equity and Bonds

(a) Daily Returns of Equity Indices

	Release	Nonrelease	All Days
SP500 Ex-Financial			
Mean	0.01	0.03	0.02
	(0.05)	(0.02)	(0.02)
Std Deviation	1.24	1.20	1.20
	(0.03)	(0.01)	(0.01)
Observations	635	5,655	6,290
SML			
Mean	0.05	0.03	0.03
	(0.06)	(0.02)	(0.02)
Std Deviation	1.51	1.47	1.48
	(0.04)	(0.01)	(0.01)
Observations	635	5,654	6,289
Russell			
Mean	0.04	0.02	0.02
	(0.06)	(0.02)	(0.02)
Std Deviation	1.60	1.53	1.53
	(0.04)	(0.01)	(0.01)
Observations	635	5,654	6,291

(b) Daily Changes in Bond Spreads

	Release	Nonrelease	All Days
Excess bond premium			
Mean	-0.27	-0.00	-0.03
	(0.37)	(0.12)	(0.11)
Std Deviation	8.31	7.91	7.95
	(0.27)	(0.08)	(0.08)
Observations	492	4,441	4,933
Investment grade			
Mean	-0.13	0.03	0.01
	(0.10)	(0.03)	(0.03)
Std Deviation	2.60	2.64	2.64
	(0.07)	(0.02)	(0.02)
Observations	634	5,992	6,626
High yield			
Mean	-0.75	0.11	0.03
	(0.42)	(0.13)	(0.12)
Std Deviation	10.62	10.10	10.15
	(0.30)	(0.09)	(0.09)
Observations	634	5,992	6,626
CCC constituents			
Mean	1.20	1.80	1.74
	(0.29)	(0.10)	(0.09)
Std Deviation	110.09	106.81	107.17
	(0.20)	(0.07)	(0.06)
Observations	146,670	1,238,294	1,384,964
N Bonds	3,308		

Notes: Panel (a) shows descriptive statistics (in percent) of daily returns of equity indices (S&P 500 Ex-Financials, S&P Small Cap 600, and Russell 2000). Returns are computed as daily log differences. Panel (b) shows descriptive statistics (in basis points) of daily changes in the excess bond premium, option-adjusted spreads of ICE BofA's investment-grade and high-yield indices of U.S. corporate bonds, and option-adjusted spreads for nonfinancial constituent bonds in ICE BofA's CCC & Lower index. "Release Days" refers to days with earnings releases by financial intermediaries in the sample; "Nonrelease Days" refers to days without earnings releases; "All Days" includes both release days and nonrelease days. Standard errors are in parentheses.

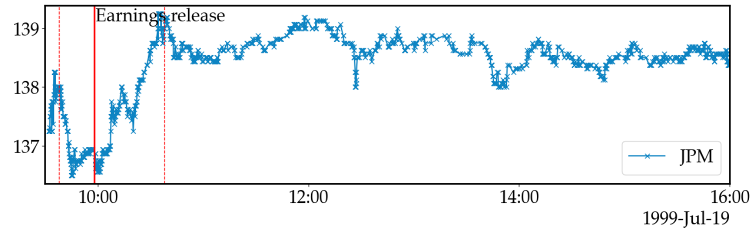
Table B.2: Bond Holdings by Intermediary

Intermediary	Mean	SD	Min	Max	Intermediary	Mean	SD	Min	Max
J.P. Morgan Chase	2.6	8.7	0	100	Wells Fargo	0.3	2.3	0	100
Goldman Sachs	0.9	3.1	0	62	BNY Mellon	0.3	2.6	0	100
Ameriprise Financial	0.8	3.4	0	100	Merrill Lynch	0.1	1.7	0	82
Morgan Stanley	0.5	4.6	0	100	U.S. Bancorp	0.003	0.03	0	1
Citicorp	0.4	3.1	0	93	Bank of America	0.001	0.04	0	1
Northern Trust	0.3	1.8	0	93					
All	6.0	12.0	0	100					

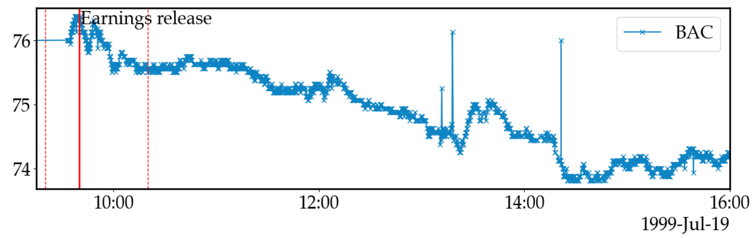
Notes: This table shows descriptive statistics for the shares of bonds held by financial intermediaries, displayed in percent. The set of bonds includes bonds rated CCC or lower in ICE issued by firms with at least 10 bonds outstanding.

Figure B.1: Construction of Broad Financial Shocks

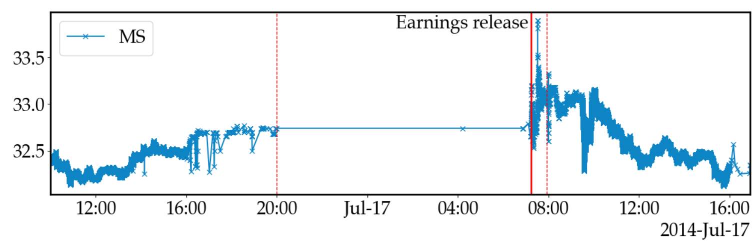
(a) Median Positive Shock (Inside Regular Trading Hours)



(b) Median Negative Shock (Inside Regular Trading Hours)



(c) Median Positive Shock (Outside Regular Trading Hours)



(d) Median Negative Shock (Outside Regular Trading Hours)

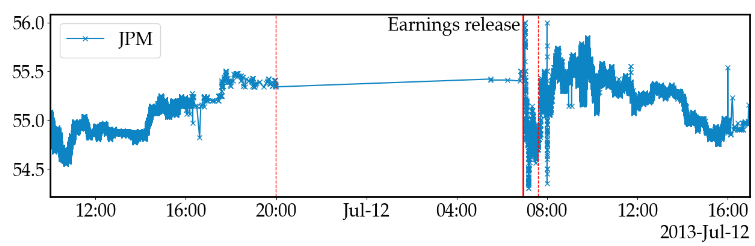
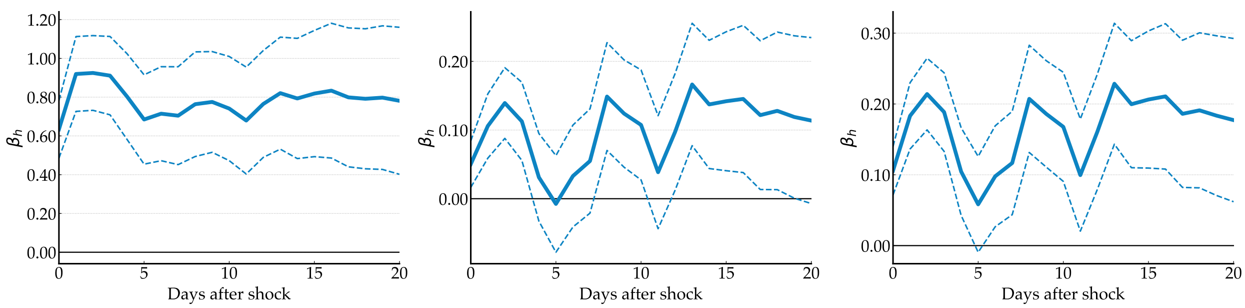


Figure B.2: The Pass-Through of Broad Financial Shocks on the Financial Sector's Market Value

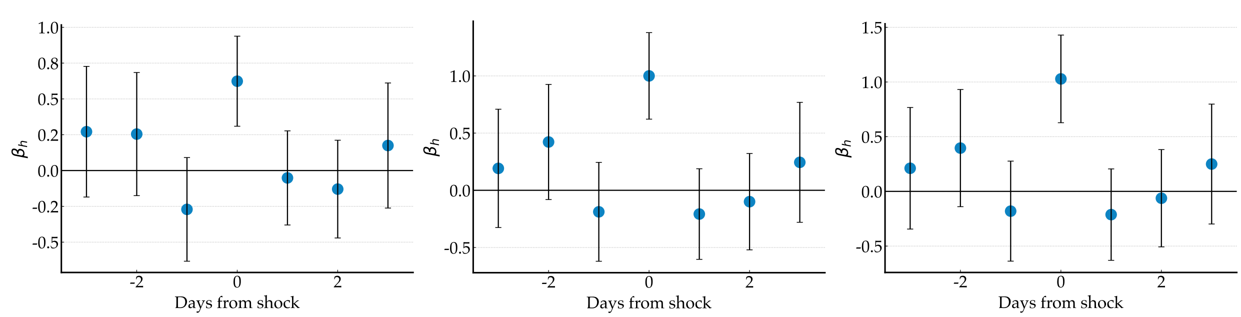
(a) Reporting Intermediaries **(b)** Nonreporting Intermediaries **(c)** All Intermediaries



Notes: The figures show the cumulative responses of financial intermediaries' market capitalization to individual unweighted financial shocks, $\Delta p_{i,\mathrm{F},t}$. Panel (a) reports the market capitalization response from the intermediary i that reports the earnings underlying the financial shock by estimating: $\log V_{it+h} - \log V_{it-1} = \alpha_h + \beta_h \Delta p_{i,\mathrm{F},t} + u_{ith}$, where V_{jt+h} is the market capitalization of earnings-reporting intermediary i after h days following the earnings announcement by financial intermediary i in day t; and $\Delta p_{i,\mathrm{F},t}$ is the 60-minute log stock price changes of the intermediary i. Panel (b) reports the market capitalization responses from all financial intermediaries in our sample in quarter q by estimating the local projection: $\log V_{jt+h} - \log V_{jt-1} = \alpha_h + \beta_h \Delta p_{i,\mathrm{F},t} + u_{ith}$, where V_{jt+h} is the market capitalization of intermediary $j \in \mathcal{I}_q$ after h days following the earnings announcement by financial intermediary i in day t; and $\Delta p_{i,\mathrm{F},t}$ is the 60-minute log stock price changes of the earnings-reporting intermediary i. Panel (c) reports the market capitalization response from all remaining nonreporting intermediaries by estimating a variant of the local projection in panel (b), where $j \in \mathcal{I}_q$ and $j \neq i$. Dashed lines represent 90% confidence intervals.

Figure B.3: Placebo Tests: Nonfinancial Firms' Stock Price and Broad Financial Shocks on Nonevent Days

(a) S&P 500 Ex-Fin **(b)** SmallCap 600 **(c)** Russell 2000



Notes: The figures show placebo tests with nonevent days. Specifications take the form $\Delta \log y_{t+h} = \alpha_h + \beta_h v_{\mathrm{F,t}} + u_{th}$. Changes in dependent equity indices are constructed using alternative dates $h = -3, \cdots, 3$ around the event date, with $h = 0$ corresponding to the event date of earnings releases. 95% confidence intervals are reported.

Table B.3: Financial Shocks vs. Placebo Dow Jones Shocks

(a) Financial Shocks

	S&P 500	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{F,t}}$	0.741***	1.196***	1.263***	390
	(0.199)	(0.250)	(0.260)	
$v_{\mathrm{F,t}}$ (incl. announcements	0.624***	1.000***	1.028***	635
outside of trading hours)	(0.157)	(0.189)	(0.200)	

(b) Placebo Dow Jones Nonfinancial Shocks

	S&P 500	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{NF,t}}$	-0.026	-0.230	-0.227	801
	(0.189)	(0.234)	(0.241)	
$v_{\mathrm{NF,t}}$ (incl. announcements	0.287*	0.105	0.135	1146
outside of trading hours)	(0.169)	(0.201)	(0.208)	

(c) Placebo Dow Jones Nonfinancial Shocks
(Equal Number of Placebo Firms per Quarter as Financial Intermediaries)

	S&P 500	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{NF,t}}$	-0.018	-0.150	-0.146	554
	(0.152)	(0.193)	(0.198)	
$v_{\mathrm{NF,t}}$ (incl. announcements	0.224	0.099	0.126	831
outside of trading hours)	(0.146)	(0.175)	(0.180)	

Notes: This table shows results from estimating $\Delta \log y_t = \alpha + \beta v_{\mathrm{F,t}} + u_t$, where $\Delta \log y_t$ is the daily log change in one of the following indices: S&P 500 Ex-Financials, S&P SmallCap 600, or Russell 2000. Panel (a) shows the estimates for β using broad financial shocks, described in the main text. Panel (b) shows placebo tests with high-frequency shocks generated by nonfinancial firms in Dow Jones. Shock construction and regression specifications follow those for broad financial shocks. Firms are 3M, Alcoa, Altria, Philip Morris, Apple, Amgen, AT&T, Bethlehem Steel, Boeing, Caterpillar, Chevron, Cisco, Coca-Cola, Dow, Dupont, Eastman Kodak, Exxon, FW Woolworth, General Electric, General Motors, Goodyear, Hewlett-Packard, Home Depot, Intel, IBM, International Paper, Johnson & Johnson, Kraft, McDonald's, Merck, Microsoft, Nike, Pfizer, Procter & Gamble, Raytheon, Salesforce, Sears, Texaco, Union Carbide, United Technologies, UnitedHealth, Verizon, Visa, Walgreens, Walmart, Walt Disney, and Westinghouse. Panel (c) shows placebo tests with high-frequency shocks generated based on the biggest Dow Jones nonfinancial firms by market value, so that the number of Dow Jones firms included in the placebo shocks equals the number of financial intermediaries included in the financial shocks. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table B.4: Effects of High-Frequency Placebo Shocks with S&P 500 Nonfinancial Firms

Dependent Variables	**Placebo Sectors**	**Effects of Placebo Shocks**
SP500 Ex-Energy Index	Energy	-0.724
		(0.611)
SP500 Ex-Materials Index	Materials	-1.219
		(0.956)
SP500 Ex-Industrials Index	Industrials	0.509
		(1.131)
SP500 Ex-Consumer Discretionary Index	Consumer Discretionary	0.315
		(0.658)
SP500 Ex-Consumer Staples Index	Consumer Staples	0.191
		(0.518)
SP500 Ex-Healthcare Index	Healthcare	1.166
		(0.875)
SP500 Ex-Information Technology Index	Information Technology	0.166
		(0.813)
SP500 Ex-Communication Services Index	Communication Services	0.177
		(0.365)
SP500 Ex-Utilities Index	Utilities	-1.487
		(1.246)
SP500 Ex-Real Estate Index	Real Estate	1.497
		(1.457)

Notes: This table reports the effects of placebo high-frequency shocks. For each nonfinancial sector s of the S&P 500, the placebo high-frequency shock v_t^s is constructed following the procedure for broad financial shocks described in Section 3. The specification estimated is $\Delta \log y_t^{-s} = \alpha + \beta v_t^s + u_{st}$ for each sector $s \in$ {energy, materials, information technology, ...}, where v_t^s is the placebo high-frequency shock and y_t^{-s} is the equity index that excludes the placebo shock sector. Standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table B.5: Comparison of Event-study framework and Heteroskedasticity-based Identification

Fin Shock	**Freq**	**Dependent Variable**	**Freq**	**OLS**	**Heteroske-dasticity**
Reporting intermediaries	60-min	S&P 500 nonfin constituents (equal weighted)	60-min	0.245** (0.104)	- -
All intermediaries	60-min	S&P 500 nonfin constituents (equal weighted)	60-min	0.190*** (0.052	0.410*** (0.027)
All intermediaries	60-min	S&P 500 nonfin constituents (value weighted)	60-min	0.186*** (0.050)	0.362*** (0.027)
All intermediaries	60-min	S&P 500 index ETF	60-min	0.151*** (0.025)	0.372*** (0.026)
All intermediaries	60-min	S&P 500 nonfin index	daily	0.538*** (0.079)	- -
All intermediaries	daily	S&P 500 nonfin index	daily	- -	0.434*** (0.022)

Notes: This table compares empirical results obtained from event-study framework and heteroskedasticity-based identification for various combinations of frequency, definitions of financial shocks, and weighting of dependent variables. A specification that is infeasible for an identification strategy is omitted. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table B.6: Heterogeneous Firm Responses to Financial and Monetary Shocks

(a) Monetary Shocks

	(1) **Average**	(2) **Leverage** (High)	(3) **Credit Ratings** (Invt Grade)	(4) **Liquidity** (Liquid)
$v_{\mathrm{M},t}$	2.205***	2.544***	2.919***	2.125***
	(0.670)	(0.711)	(1.051)	(0.635)
		(0.011)	(0.066)	(0.011)
$v_{\mathrm{M},t} \times x_{jt-1}$		-0.699***	1.379**	0.160
		(0.225)	(0.530)	(0.138)
Adjusted R^2	0.028	0.028	0.070	0.028
Observations	159,723	159,723	38,425	159,703
Firm controls	no	yes	yes	yes
Quarter-sector FE	no	no	no	no
Double-clustered SE	yes	yes	yes	yes

(b) Financial Shocks

	(1) **Average**	(2) **Leverage** (High)	(3) **Credit Ratings** (Invt Grade)	(4) **Liquidity** (Liquid)
$v_{\mathrm{F},t}$	0.247***	0.240***	0.362***	0.250***
	(0.079)	(0.090)	(0.133)	(0.087)
$v_{\mathrm{F},t} \times x_{jt-1}$		0.015	-0.088**	-0.006
		(0.014)	(0.043)	(0.015)
Adjusted R^2	0.025	0.025	0.040	0.025
Observations	750,260	750,260	162,281	750,241
Firm controls	no	yes	yes	yes
Firm FE	yes	yes	yes	yes
Quarter-sector FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

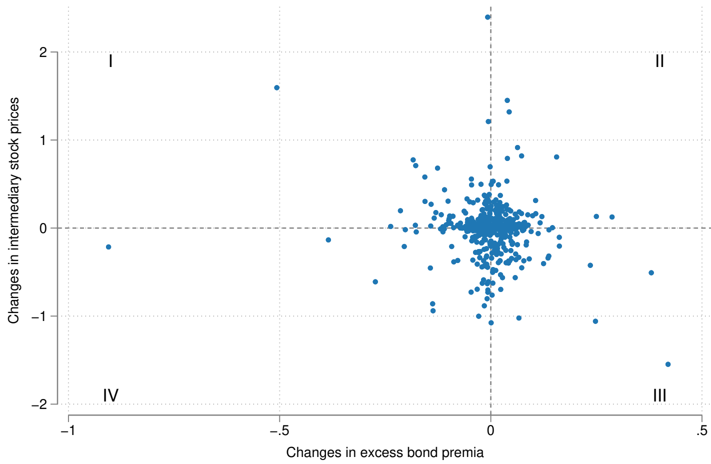
Notes: This table reports results from estimating

$$\Delta y_{jt} = \alpha_j + a_{sq} + \beta_M v_{\mathrm{M},t} + \gamma_M v_{\mathrm{M},t} x_{jt-1} + \Gamma' Z_{jt-1} + u_{jt} \qquad \text{(monetary)}$$

$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta_F v_{\mathrm{F},t} + \gamma_F v_{\mathrm{F},t} x_{jt-1} + \Gamma' Z_{jt-1} + u_{jt} \qquad \text{(financial)}$$

where $v_{\mathrm{M},t}$ and $v_{\mathrm{F},t}$ denote high-frequency financial and monetary shocks, respectively; x_{jt-1} is an indicator variable for high leverage, investment-grade credit ratings, or high liquidity; and Z_{jt-1} is a vector of firm controls—the firm characteristic x_{jt-1}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. The broad financial shock, $v_{\mathrm{F},t}$, is constructed as described in the text. The high-frequency monetary shock, $v_{\mathrm{M},t}$, is constructed based on changes in federal funds futures in a 60-minute window around a Federal Open Market Committee announcement, as in Gorodnichenko and Weber (2016). We normalize the sign of the monetary shock so that a positive shock corresponds to a decrease in the interest rate. The sample period for monetary shocks stops in 2007 to focus on conventional monetary policy. The dependent variable, Δy_{jt}, is log changes in firms' stock prices in the corresponding 60-minute window around the monetary/financial announcement. Leverage is defined as the ratio of total debt to total assets. Liquidity is defined as the ratio of cash and short-term investment to total assets. Leverage and liquidity are demeaned and standardized at firm level so that the units are standard deviations. Credit ratings are measured as S&P's long-term issue rating of the firm and follow S&P's definition of investment grade as BBB or better and speculative grade as BB or worse. Standard errors are two-way clustered at shock and firm level and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure B.4: Scatterplot of event-time changes in stock prices and excess bond premia



We estimate an event-study regression with the decomposed shocks to examine the importance of each component of broad financial shocks:

$$\Delta y_t = \alpha + \beta_{\mathrm{CS}} v_{\mathrm{CS,t}} + \beta_{\mathrm{CD}} v_{\mathrm{CD,t}} + u_t, \tag{23}$$

where Δy_t is the daily change in the S&P 500 Ex-Financials Index.

Table B.7: Decomposition of broad financial shocks with sign restrictions

	(1) **SP500**	(2) **Ex-Fin**
Givens rotation matrix		
$v_{\mathrm{F,purged}}$	1.276***	
	(0.305)	
$v_{\mathrm{F,res}}$	0.067	
	(0.389)	
Poor man's sign restrictions		
$v_{\mathrm{F,purged}}$		1.100***
		(0.251)
$v_{\mathrm{F,res}}$		0.294
		(0.305)
R^2	0.068	0.053
Observations	492	492
Robust SE	yes	yes

Notes: This table reports β_{CS} and β_{CD} from estimating $\Delta y_t = \alpha + \beta_{\mathrm{CS}} v_{\mathrm{CS,t}} + \beta_{\mathrm{CD}} v_{\mathrm{CD,t}} + u_t$, where Δy_t is daily changes in the S&P 500 Ex-Financials Index, v_{CS} is the shock to the supply of credit, and v_{CD} is the shock to the demand for credit. $v_{\mathrm{CS,t}}$ and $v_{\mathrm{CD,t}}$ are decomposed using sign restrictions as specified in the text and implemented using three different methods, which include Givens rotation matrices and the poor man's sign restrictions. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C. Content of High-Frequency Broad Financial Shocks

In this section, we provide supportive evidence on the content of broad financial shocks.

C.1. Unexpected earnings and broad financial shocks

Figure C.1 depicts the relationship between surprise earnings and broad financial shocks. We measure surprise earnings using the standardized unexpected earnings following the post-earnings-announcement-drift literature (see, for example, Chordia and Shivakumar, 2006), defined as the difference between the reported earnings per share and the consensus forecast, normalized by the standard error of analysts' forecast errors. We obtain data on reported earnings and analysts' forecasts from IBES.

For each earnings announcement, we compare the unexpected earnings of financial institutions with their high-frequency stock price movements used to construct the broad financial shocks. Figure C.1 shows that stock price movements from financial institutions tend to be positively associated with their surprise earnings, which suggests that broad financial shocks encode the information on earnings released in the announcements.

Figure C.1: Earnings surprises and broad financial shocks

Notes: This figure shows a binned scatter plot between broad financial shocks and earnings surprises with 50 bins. Broad financial shocks are unweighted and constructed as described in the main text. Earnings surprises are measured as standardized unexpected earnings, as defined in the text.

Table C.1: Transmission from earnings surprises to releasing intermediary stock price change

	Financial Shocks	**Placebo Shocks**
Earnings surprises	0.217*** (0.032)	0.233*** (0.069)
R^2	0.040	0.010
Obs.	1,109	1,150

Notes: This table reports estimates from regressing unweighted changes in the stock prices of financial intermediaries and placebo nonfinancial firms in Dow Jones. Earnings surprises are measured with standardized unexpected earnings, defined in the text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C.2. Predictability of broad financial shocks

In this section, we use a state-of-the-art machine-learning model to provide evidence suggesting that broad financial shocks are not predictable using the macroeconomic and financial variables available prior to the shock. We use two sets of predictors. The first macro panel contains a large panel of 126 monthly macroeconomic series constructed by McCracken and Ng (2016) and available through FRED-MD. The second financial panel is of higher daily frequency and includes stock prices of the financial intermediaries in our sample, as well as the S&P 500 and VIX.

Our main forecasting model is random forests (Breiman, 2001), which produce an average prediction from a large collection of regression trees. Random forests incorporate nonlinearity and multi-way interactions between predictors, which renders the method useful for macroeconomic and financial forecasting (Gentzkow, Kelly and Taddy, 2019). The random-forest predictor is defined as

$$\hat{f}_{\text{rf}}^{B} = \frac{1}{B}\sum_{b=1}^{B} T(x;\Theta_b),$$

which averages the forecasts of B regression trees $T(x;\Theta_b)$, where x is the set of predictors and Θ_b characterizes the parameters in the bth tree.[17]

As Gentzkow *et al.* (2019) argue, the benefits of regression trees from nonlinearity and high-order interactions lessen with high-dimensional predictors, so we first perform variable selection with elastic net (Zou and Hastie, 2005), which is an implementation of soft thresholding regularization that drops uninformative predictors using penalized regressions. The elastic net estimator is defined

[17] See Hastie, Tibshirani and Friedman (2009) for a comprehensive exposition of trees and random forests.

by

$$\hat{\beta}_{\text{EN}} = \arg\min_{\beta} \left\{ \frac{1}{2} \sum_{i=1}^{N} (y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \left(\frac{1}{2}(1-\alpha)\|\beta\|_{l_2}^2 + \alpha\|\beta\|_{l_1} \right) \right\},$$

which minimizes the sum of regression residuals and a penalty term, which is a weighted average of LASSO and ridge. Following Borup and Schütte (2020), we set $\alpha = 0.5$ for an equal weight between LASSO and ridge regressions and tune the penalty parameter λ so that the elastic net selects the 20 best predictors.

We then use random forests to form predictions using 48-month rolling windows for macro predictors and quarter rolling windows for financial predictors. To assess forecastability, we compare the predictions from random forests with those from a random walk, formed with stock returns 1 day before the financial shock converted to match the size of the 60-minute shock window. The metric for evaluating forecastability is the out-of-sample R^2 (Campbell and Thompson, 2008), defined as

$$R^2_{\text{oos}} = 1 - \frac{\Sigma_t (y_t - \hat{y}_{m,t})^2}{\Sigma_t (y_t - \bar{y}_t)^2},$$

where $\bar{y}_t$ is the rolling-mean forecast computed on a window that matches the model-estimation window and $\hat{y}_{m,t}$ is the forecast from the model. R^2_{oos} lies in the range $(-\infty, 1]$, with negative numbers indicating that the model underperforms the historical mean of the series.

Assessments of the forecastability of broad financial shocks by macroeconomic and financial predictors are shown in Table C.2. Random-forest forecasts with both macro and financial predictors have negative R^2_{oos}, which suggests worse performance than historical rolling-mean forecasts. The results also suggest that incorporating panels of macro and financial variables does not help in forecasting broad financial shocks compared with a random walk.

Table C.2: Out-of-sample R^2 of Predictions of Broad Financial Shocks

	Macro	**Financial**
Random forest	−15.7%	−16.9%
Random-walk benchmark		−5.2%

Notes: This table reports the out-of-sample R^2 of random-forest forecasts based on a large panel of macroeconomic and financial variables compared with the out-of-sample R^2 of random-walk forecasts based on the stock returns 1 day before the shock. The out-of-sample R^2 is defined as $R^2_{\text{oos}} = 1 - \frac{\Sigma_t (y_t - \hat{y}_{m,t})^2}{\Sigma_t (y_t - \bar{y}_t)^2}$, where $\bar{y}_t$ is the rolling-mean forecast computed on a window that matches the model-estimation window, and $\hat{y}_{m,t}$ is the forecast from the model. Negative numbers indicate that the forecast underperforms the rolling historical mean of the series.

C.3. Relationship of broad financial shocks within quarters

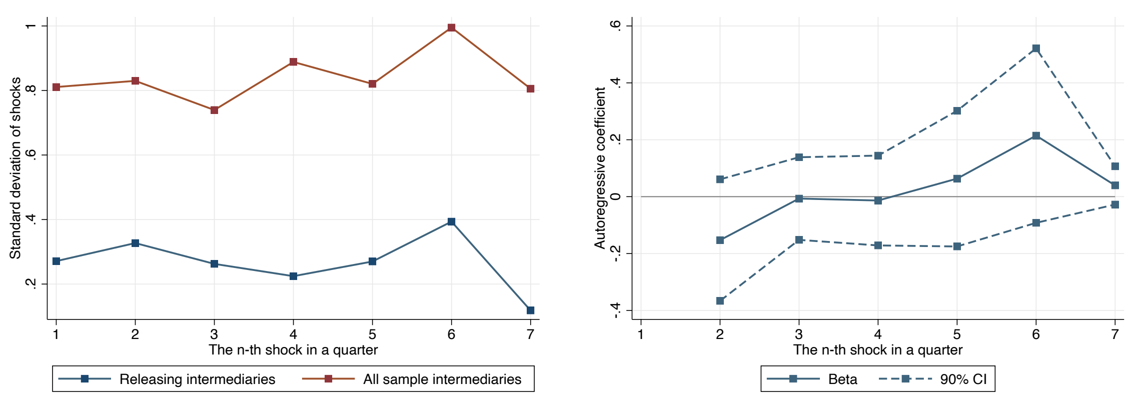
Panel (a) in Figure C.2 reports the standard deviation of the n-th broad financial shocks in a quarter, with the broad financial shocks based on earnings-releasing intermediaries in blue and those based on all sample intermediaries in red. Stock price movements around the first financial earnings announcements in a quarter display a similar variation to that of movements around subsequent announcements, which suggests that variation in the news content contained in financial announcements does not depend on the order of the scheduled announcements.

Panel (b) reports the correlation of shocks within a quarter. We estimate the autocorrelation of the n-th broad financial shocks in quarter q by regressing $v_{\mathrm{F},q(n)} = c_n + \beta_n v_{\mathrm{F},q(n-1)} + u_{n,q}$ and report the point estimates for β_n's along with their 90% confidence intervals. We find no evidence of autocorrelation in broad financial shocks. The autoregressive coefficients are statistically indistinguishable from zero, regardless of whether earnings are announced first or subsequently in a quarter.

Figure C.2: Relationship of Broad Financial Shocks Within Quarters

(a) Standard Deviation

(b) Autoregressive Coefficient



Notes: Panel (a) reports the standard deviation for the n-th broad financial shock in a quarter. Panel (b) reports the regression coefficents, β_n, from estimating $v_{\mathrm{F},q(n)} = c_n + \beta_n v_{\mathrm{F},q(n-1)} + u_{n,q}$ for the n-th broad financial shock in quarter q.

C.4. Textual analysis of broad financial shocks

We conduct three textual analyses to provide evidence that market participants interpret the earnings as being driven by idiosyncratic factors related to intermediaries and not by macroeconomic factors. Our textual sample is based on the *Wall Street Journal*'s (WSJ) coverage of intermediaries' earnings announcements. We search Factiva, a news database, and the WSJ's online archive for articles corresponding to the financial earnings announcements included in our sample and collect a textual sample of 807 articles. We remove metadata, such as the dates of articles, names of reporters, and alt text of pictures, to form the corpus for analysis.

C.4.1. Sentiment analysis

The first exercise asks whether broad financial shocks capture the market sentiment of an intermediary's earnings outcome. To answer this question, we measure textual sentiment in the news covering an intermediary's earnings result and analyze the relationship between textual sentiment and the earnings result and stock price movements.

The sentiment of the WSJ's reporting on an earnings release is measured using the Loughran and McDonald (2011) dictionary updated in 2018, which categorizes words into four sentiments (positive, negative, uncertain, or of no particular sentiment). Compared with other dictionaries, such as the Harvard IV-4 dictionary and Lasswell value dictionary, Loughran and McDonald (2011) categorize sentiment specific to an economic context and is widely adopted in macro and financial applications (see, for example, Hassan, Schwedeler, Schreger and Tahoun, 2021). We measure positive (negative) sentiment as the percentage of positive (negative) words of all unique words in a news piece. For robustness, we construct an additional measure of positive sentiment as the percentage of positive minus negative words of all unique words.

Table C.3a reports the relationship between the surprise component of earnings and the news sentiment of the underlying earnings releases. It shows that better-than-expected earnings are associated with more positive coverage, which suggests that market sentiment as measured through WSJ coverage focuses primarily on the earnings outcome. Table C.3b reports the relationship between unweighted broad financial shocks and news sentiment. It shows that broad financial shocks capture the market sentiment, as measured through WSJ coverage. More positive news coverage is associated with more positive movements in the intermediary's stock prices within a narrow window, and more negative news coverage is associated with more negative movements in the stock prices.

C.4.2. Topic modeling

The second exercise asks whether market participants attribute earnings outcomes to intermediaries' idiosyncratic performance or to macroeconomic factors. To answer this question, we use a latent Dirichlet allocation (LDA) model (Blei, Ng and Jordan, 2003) to detect topics discussed in the WSJ's coverage of the earnings release.

LDA is a Bayesian factor model aimed at reducing high-dimensional text into a few "topics" or factors. Documents are represented as random mixtures of latent topics. Given D documents that constitute a corpus of text with V unique vocabulary and K topics, each topic k is represented by a distribution over the vocabulary $\beta_k \in \Delta^{V-1}$, and each document d is represented by a distribution over the topics θ_d^k. LDA assumes a generative process for each document and places Dirichlet priors on β_k and θ_d. The limited inputs imposed by researchers and the high interpretability of its output make it a valuable tool for detecting themes in economic text (Hansen, McMahon and Prat, 2018; Larsen and Thorsrud, 2019; Bybee, Kelly, Manela and Xiu, 2021).

We preprocess the text to reduce the vocabulary to a set of terms that are most likely to answer the question: Do market participants attribute earnings outcomes to intermediary-specific factors or macroeconomic factors? To that end, we first transform individual bank names into a single token (for example, `JP Morgan Chase` and `Goldman` are both converted to the token `bankname`). Next, we remove numeric values, stop words (such as `a` and `the`), capitalization, and tokens that have fewer than 3 characters, appear fewer than 5 times, or appear in more than 80% of the documents, and lemmatize the tokens (for example, `increases` and `increase` are both lemmatized to `increase`). The advantage of lemmatization over stemming is that it produces more human-friendly output. Finally, we add to the vocabulary phrases (bigrams) whose frequency is higher than 10.

We estimate the LDA model using the online variational Bayes algorithm developed by Hoffman, Bach and Blei (2010) and assign symmetric Dirichlet priors. An important parameter of the model is the number of topics K. We choose K to maximize the topic coherence score (Röder, Both and Hinneburg, 2015), so that the topics produced by the model are most likely to be interpretable. Figure C.3b shows that $K = 3$ is the optimal choice of topic numbers under this criterion.

Figure C.3a reports the topics detected by the LDA model. All three topics center on an intermediary's idiosyncratic performance. The first two topics focus on loans and mortgages—the core business areas of commercial banks—and the last topic focuses on investment banking and trading. None of the topics, however, relate to the macroeconomy, which indicates that the WSJ attributes earnings outcomes to factors specific to intermediaries rather than to macroeconomic fluctuations.

C.4.3. Narratives

The last textual analysis provides further context for narratives related to earnings. We focus on the coverage of individual banks and study what market participants perceive as the causes and consequences of earnings. We focus on three banks with the most WSJ coverage (J.P. Morgan, Goldman Sachs, and Wells Fargo) and analyze the causal stories constructed in the coverage of each bank with the algorithm based on `relatio` developed by Ash, Gauthier and Widmer (2021).

The unit of analysis is a sentence. The first step in the analysis is to reduce the dimensionality by grouping terms that tend to convey the same meaning. As part of the dimensionality reduction, we perform text preprocessing by converting variants of an intermediary's name to its stock ticker (for example, `Goldman`, `Goldman Sachs` and `Goldman Sachs Group` are all converted into the token `GS`). We also convert dollar amounts (such as $200 million) and percentages (such as 2.5%) into single tokens of `dollaramount` and `percentamount`, respectively. After the preprocessing, we tag named identities (such as person names and organizations) and use the K-means algorithm to cluster terms with the same sentence embeddings. The goal of this step is to transform terms with similar meanings, such as `earnings` and `earnings outcome`, into a single token. In the estimation, we specify the number of named entities and cluster to both be 50.

The second and central step of the analysis is the semantic role labeling of a sentence, which labels *who* is doing *what* to *whom* in a sentence. It labels the agent ("who"), the verb ("what"), and the object ("whom"). With this step, we can study the causes market participants attribute intermediaries' earnings results to.

Figure C.4 plots the top 30 narratives for each intermediary. On close inspection of the coverage of the three intermediaries, narratives related to their earnings announcement fall into three categories. The first summarizes the earnings result (e.g., "bank report result," "bank highlight strong"). The second relates earnings to market expectations (e.g., "result surpass expectation," "thomson poll analyst"). The last analyzes the drivers of earnings (e.g., "attractive business risk capability hold revenue," "bank report organic growth," "bank cut loan," "bank drop credit loss provision"). Of the narratives in the last category, which analyze the causes of earnings, none revolves around macroeconomic factors and all discuss intermediary-specific factors.

Table C.3: News Sentiment, Earnings Surprises, and Broad Financial Shocks

(a) News Sentiment and Earnings

	(1)	(2)	(3)
	Earnings Surprises		
% Positive	0.800***		
	(0.115)		
% Negative		-0.492***	
		(0.055)	
% (Positive − Negative)			0.459***
			(0.042)
Observations	710	710	710
R^2	0.097	0.088	0.137

(b) News Sentiment and Stock Prices

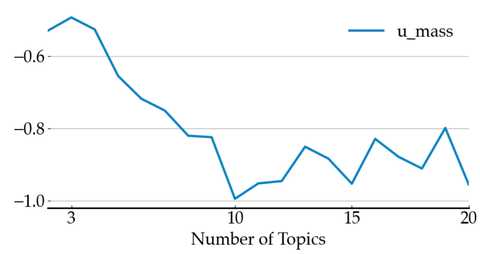
	(1)	(2)	(3)
	Change in Stock Prices		
% Positive	0.432***		
	(0.103)		
% Negative		-0.143*	
		(0.081)	
% (Positive − Negative)			0.179***
			(0.057)
Observations	710	710	710
R^2	0.022	0.006	0.017

Notes: Panel (a) reports the relationship between standardized surprise earnings and WSJ textual sentiment. Panel (b) reports the relationship between high-frequency changes in stock prices and WSJ sentiment. Three measures of textual sentiment in WSJ coverage are reported: percentage of unique positive/negative/positive minus negative tokens of all unique words in an article, respectively. Robust standard errors are in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure C.3: LDA Topics in Earnings Coverage

(a) LDA Topics

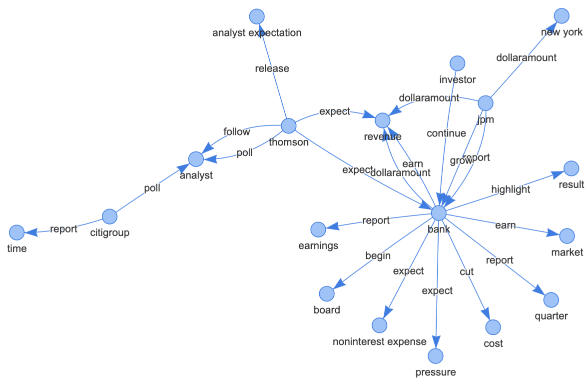
(b) Topic Coherence



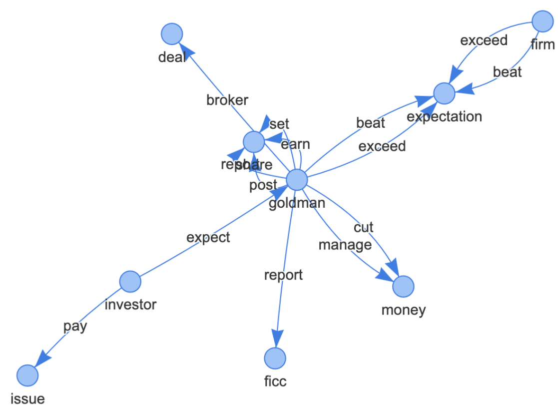
Notes: Panel (a) reports all three topics detected by the LDA model in WSJ articles. A larger font size represents a higher probability of a word or bigram appearing in an article. Panel (b) plots topic coherence measured against the number of topics K. Topic coherence is measured by $u_{\text{mass}} = \frac{2}{V(V-1)} \sum_{i=2}^{V} \sum_{j=1}^{i=1} \log \frac{P(w_i, w_j)+\varepsilon}{P(w_j)}$, where (w_i, w_j) represent a pair of vocabulary.

Figure C.4: Narratives in Earnings Coverage

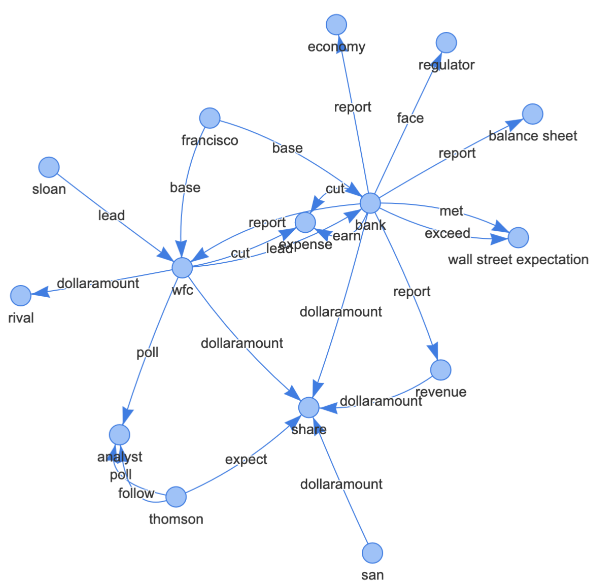
(a) J.P. Morgan



(b) Goldman Sachs



(c) Wells Fargo



C.5. Stock-price volatility for financial intermediaries and nonfinancial firms: Event vs. nonevent days

Table C.4 reports descriptive statistics for the stock price of financial intermediaries and nonfinancial firms in the S&P 500 during event windows in which intermediaries release earnings and nonevent windows. It shows that the volatility of financial intermediaries' stock prices during their earnings announcements increases by substantially more than those of nonfinancial firms during these events, which is consistent with the fact that intermediaries' earnings announcements contain more information about financial intermediaries than about nonfinancial firms.

Table C.4: Summary Statistics for Event and Nonevent Windows

	Financial Intermediaries		Nonfinancial Firms	
	Release	Nonrelease	Release	Nonrelease
Mean of weighted ΔP	0.11	0.05	0.02	0.04
	(0.02)	(0.00)	(0.01)	(0.00)
SD of weighted ΔP	0.74	0.67	0.46	0.42
	(0.02)	(0.00)	(0.01)	(0.00)
Observations	1,104	20,365	1,104	20,365

Notes: This table shows summary statistics for weighted high-frequency stock-price changes for event windows and nonevent windows. Financial intermediaries are the institutions listed in Table 1. Nonfinancial firms are constituents of the S&P 500 excluding financial firms (NAICS 52). Standard errors are in parentheses.

D. Additional Robustness Analysis

Table D.1: Stock Market's Reaction to Intermediaries' Earnings Announcements for Alternative Weighting of S&P 500 Firms and Financial Intermediaries

	(1)	(2)	(3)	(4)	(5)
	Equal-weighted		**Value-weighted**		**HF Index**
Independent variables:					
$v_{\mathrm{F},t}$	0.245**		0.200***		0.193**
	(0.104)		(0.077)		(0.079)
$\Delta p_{\mathrm{F},i,t}$		0.033***		0.028***	
		(0.011)		(0.010)	
R^2	0.012	0.013	0.005	0.006	0.011
Observations	173,475	173,475	164,132	164,132	517
Security fixed effects	yes	yes	yes	yes	no
Double clustering	yes	yes	yes	yes	no

Notes: Columns 1 and 3 of this table report estimates from the event-study regression $\Delta y_{jt} = \alpha_j + \beta v_{\mathrm{F},t} + u_{jt}$ using different weighting for the dependent variable Δy_{jt}. α_j is a CUSIP fixed effect and $v_{\mathrm{F},t}$ is the high-frequency shock. Baseline columns 1 (same as in Table 3) use the equal-weighted log price changes in S&P 500 nonfinancial constituents' stocks. Columns 3 use the log price changes in S&P 500 nonfinancial constituents' stocks weighted by their market values at the beginning of the quarter. Columns 2 and 4 of this table report estimates from the event-study regression $\Delta y_{jt} = \alpha_j + \beta \Delta p_{\mathrm{F},i,t} + u_{jt}$ using different weighting for the dependent variable Δy_{jt}. Standard errors in columns 1 through 4 are two-way clustered at shock and security levels. Column 5 replaces the CUSIP fixed effect with a constant and uses the broad S&P 500 Index at high frequency, measured through the exchange-traded fund SPDR. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D.2: Stock Market's Reaction to Intermediaries' Earnings Announcements at Daily Frequency

	S&P 500	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{F,t}}$	0.741***	1.196***	1.263***	390
	(0.199)	(0.250)	(0.260)	
$v_{\mathrm{F,t}}$ (incl. announcements	0.624***	1.000***	1.028***	635
outside of trading hours)	(0.157)	(0.189)	(0.200)	

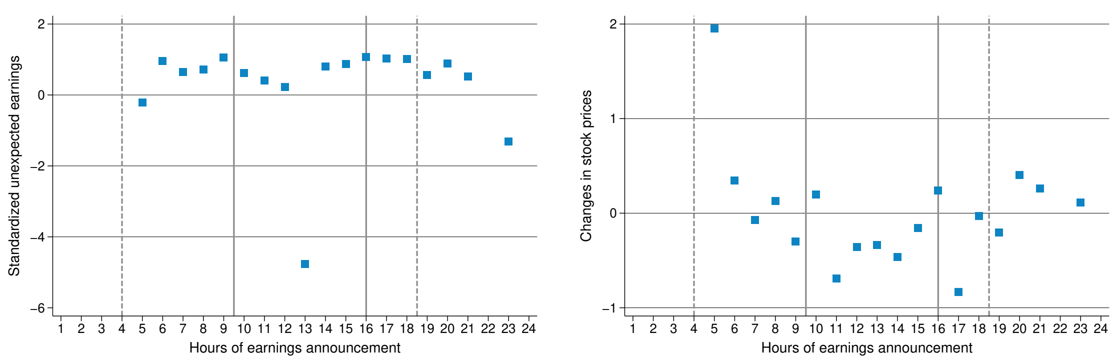
Notes: This table shows results from estimating $\Delta \log y_t = \alpha + \beta v_{\mathrm{F},t} + u_t$, where $\Delta \log y_t$ is the daily log change in one of the following indices: S&P 500 Ex-Financials, S&P SmallCap 600, or Russell 2000; and $v_{\mathrm{F},t}$ is the broad financial shock, described in the main text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D.3: Stock Market's Reaction to Intermediaries' Earnings Announcements (measure of broad financial shocks that includes earnings announced outside of trading hours)

	(1) Equal-weighted	(2) Value-weighted	(3) HF Index
Independent variable:			
$v_{\mathrm{F},t}$ (incl. announcements	0.425***	0.417***	0.443***
outside of trading hours	(0.092)	(0.088)	(0.070)
R^2	0.014	0.004	0.035
Observations	352,120	338,066	1,091
Security fixed effects	yes	yes	no
Double clustering	yes	yes	no

Notes: This table reports estimates from the event-study regression $\Delta y_{jt} = \alpha_j + \beta v_{\mathrm{F},t} + u_{jt}$ using the measure of broad financial shocks that includes earnings announced outside of trading hours. Columns 1 uses the equal-weighted log price changes of S&P 500 nonfinancial constituent stocks, as our baseline measure. Column 2 uses the log price changes in S&P 500 nonfinancial constituents' stocks weighted by their market values at the beginning of the quarter. Standard errors in columns 1 and 2 are two-way clustered at shock and security levels. Column 3 replaces the CUSIP fixed effect with a constant and used the broad S&P 500 Index at high frequency, measured through the exchange-traded fund SPDR. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure D.1: Earnings Results and Timing of Announcements



(a) Surprise earnings **(b)** Shock price changes

Notes: Panel (a) shows average standardized unexpected earnings by the hour of earnings announcement. Panel (b) shows average changes in intermediaries' stock prices by the hour of earnings announcement. Solid vertical lines represent core trading hours (9:30-16:00), and dashed vertical lines represent the hours of consolidated tape (4:00-18:30) for which the intraday data used to construct the broad financial shocks are available from TAQ.

Table D.4: Controlling for the Systemic Component between Financials and Nonfinancials

	(1)	(2)
	S&P 500 Constituents	
$v_{\mathrm{F},t}^{\text{resid}}$	0.470^{**}	
	(0.200)	
$\Delta p_{\mathrm{F},i,t}^{\text{resid}}$		0.273^{***}
		(0.076)
R^2	0.012	0.023
Observations	173,475	171,313
Security fixed effects	yes	yes
Double clustering	yes	yes

Notes: This table reports results from estimating the baseline event-study regression in (1) with the explanatory variable $v_{\mathrm{F,t}}^{\text{resid}} \equiv v_{\mathrm{F},t} - \hat{\beta}_t v_{\mathrm{F},t}$. The time-varying $\hat{\beta}_t$ is estimated by regressing the daily changes in the S&P 500 Ex-Financials Index, Δy_t, on daily changes in the S&P 500 Financials Index, $\Delta \nu_t$, in a 1-month window before the date of the earnings announcement, i.e., $\Delta y_t = \alpha + \beta \Delta \nu_t + \varepsilon_t$. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D.5: Effects of Financial Firms on Nonfinancial Firms

	(1)	(2)	(3)	(4)
	OLS	**GIV**	**OLS**	**GIV**
Financials	0.494^{***}	0.309^{***}	0.410^{***}	0.268^{***}
	(0.013)	(0.053)	(0.035)	(0.061)
R^2	0.626	0.539	0.553	0.487
Observations	5,783	5,783	489	489
Days included	all	all	earnings	earnings
Robust SE	yes	yes	yes	yes

Notes: This table shows estimates for β from fitting $\Delta y_t = \beta \Delta \nu_t + u_t$ under various specifications, where the dependent variable, Δy_t, is the S&P 500 Ex-Financials Daily Index, and the explanatory variable, $\Delta \nu_t$, is the S&P 500 Financials Daily Index. An intermediary's net worth consists of an aggregate factor, η_t, and an idiosyncratic factor, ε_{it}: $\Delta \nu_{it} = \eta_t + \varepsilon_{it}$. GIV is defined as $z_t = \sum_i s_{it} \Delta \nu_{it} - \sum_i \frac{1}{N_t} \Delta \nu_{it}$, where s_{it} is the size weight and $1/N_t$ is the equal weight. The sample period is from 1998 to 2020. Column (1) shows OLS results estimated using all daily data in the sample. Column (2) shows the estimate instrumented with the GIV using all daily data in the sample. Column (3) shows OLS results estimated using the earnings days of intermediaries included in the baseline high-frequency shocks. Column (4) shows the estimate instrumented with GIV using the earnings days of intermediaries included in the baseline high-frequency shocks. Heteroskedasiticy-robust standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D.6: State Dependency of Stock Market's Reaction to Intermediaries' Earnings Announcements (Purged Financial Shock)

	(1)	(2)	(3)
	S&P 500 Constituents		
Average ($v_{\mathrm{F,purged}}$)	1.479***		
	(0.329)		
High capitalization		0.612	0.454
		(0.668)	(0.606)
Low capitalization		1.641***	1.028**
		(0.368)	(0.522)
Adjusted R^2	0.028	0.030	0.041
Observations	207,804	207,804	207,804
Macro interactions	no	no	yes
Security fixed effects	yes	yes	yes
Double clustering	yes	yes	yes

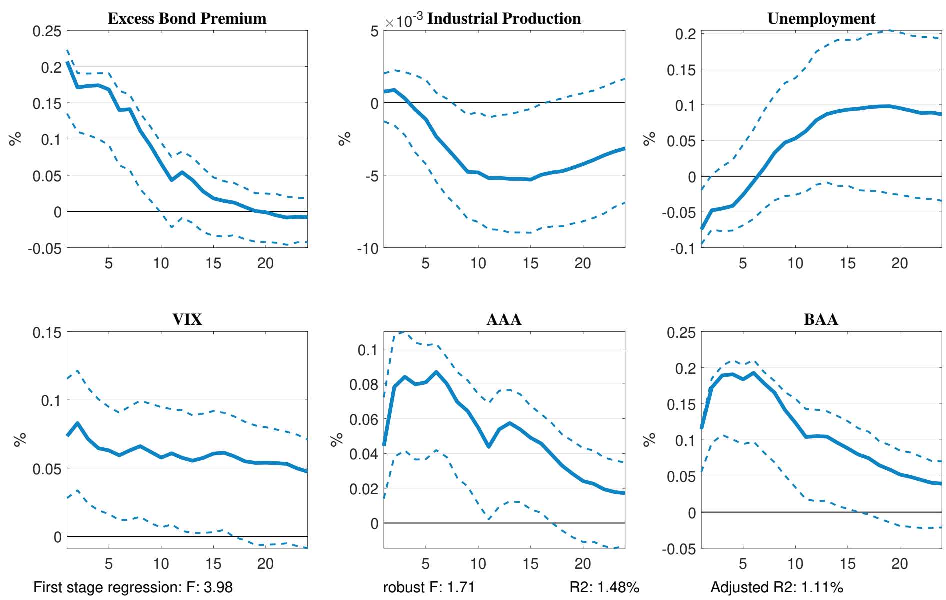
Notes: This table reports results from estimating (11): $\Delta y_{jt} = \alpha_j + \beta_h \cdot v_{\mathrm{Ft,purged}} \mathbb{1}(N_t > \bar{N}_t) + \beta_l \cdot v_{\mathrm{F},t} \mathbb{1}(N_t < \bar{N}_t) + \Gamma' Z_t + u_{jt}$, where Δy_{jt} is the daily log price change of non-financial constituent securities of the S&P 500 index, $v_{\mathrm{Ft,purged}}$ is the purged financial shock; N_t is the total equity of U.S.-charted depository institutions; and Z_t is a vector of macro controls (including output, payrolls, a recession indicator) and their interaction with broad financial shocks. Standard errors are two-way clustered at shock and security levels and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D.7: Firm Heterogeneity in Stock Market's Reaction to Intermediaries' Earnings Announcements (Purged Financial Shocks)

	Average	**Leverage** (High)	**Credit Ratings** (Invt Grade)	**Liquidity** (Liquid)
$v_{\mathrm{Ft,purged}}$	1.343***	1.206***	1.625***	1.367***
	(0.333)	(0.315)	(0.435)	(0.339)
$v_{\mathrm{Ft,purged}} \times x_{jt-1}$		0.841***	-0.256	-0.118
		(0.309)	(0.171)	(0.192)
Adjusted R^2	0.028	0.028	0.049	0.028
Observations	720,617	717,933	166,050	720,598
Firm controls	no	yes	yes	yes
Firm FE	yes	yes	yes	yes
Quarter-sector FE	yes	yes	yes	yes
Double clustering	yes	yes	yes	yes

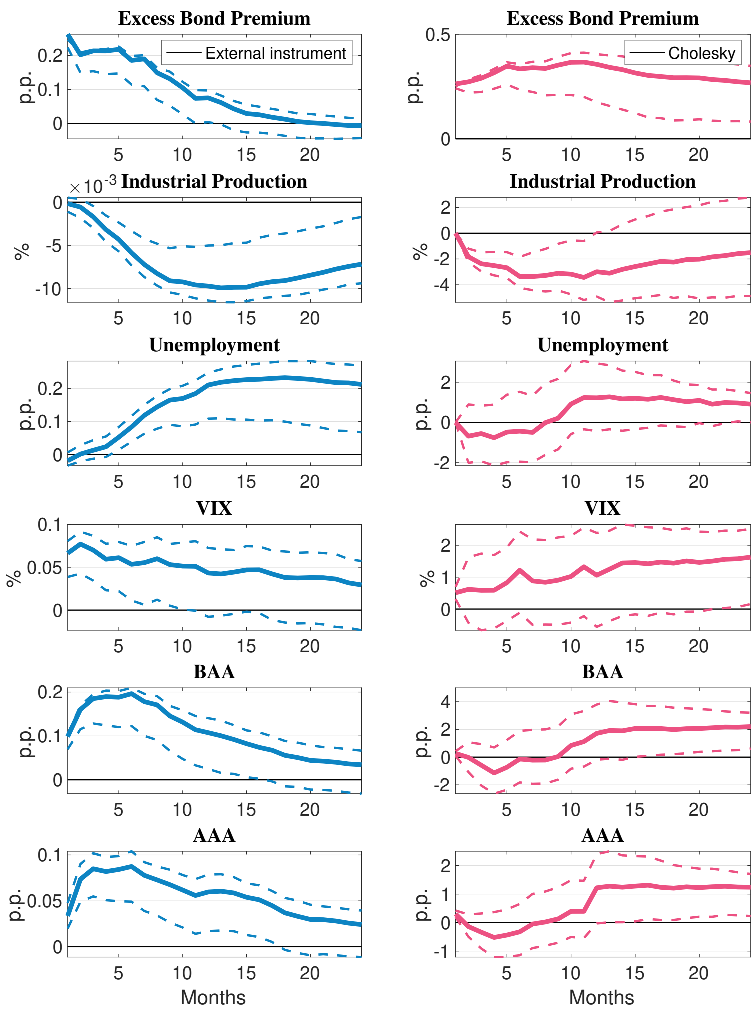
Notes: This table reports results from estimating (12): $\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta v_{\mathrm{Ft,purged}} + \gamma v_{\mathrm{Ft,purged}} x_{jt-1} + \Gamma' Z_{jt-1} + u_{jt}$, where Δy_{jt} is the 60-minute log price change of non-financial constituent securities of the S&P 500 index, $v_{\mathrm{Ft,purged}}$ is the purged financial shock as described in the main text; x_{jt-1} is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity; and Z_{jt-1} is a vector of firm controls, including firm characteristic x_{jt-1}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. Standard errors are two-way clustered at shock and security levels and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure D.2: Macroeconomic Effects using Broad Financial Shocks



Notes: This figure reports the impulse responses to a one-standard-deviation broad financial shock estimated in an external-instrument VAR. The VAR consists of the excess bond premium, log industrial production, unemployment rate, log VIX index, and the spreads between AAA- and BAA-rated bonds and 10-year treasury yields, with the excess bond premium instrumented by broad financial shocks. Dashed lines represent 90% bootstrapped confidence intervals.

Figure D.3: Comparison of external instrument and Cholesky decomposition



Notes: This figure reports impulse responses to one-standard-deviation shock to the excess bond premium in systems of VAR identified with external instrument and the Cholesky decomposition. The ordering of the Cholesky assumes that shocks to the EBP (*i*) affect macroeconomic conditions (industrial production and unemployment) with a lag, but (*ii*) can affect financial variables (VIX and bond spreads) contemporaneously. Dashed lines represent 90% confidence intervals.

E. Details for Shock Decomposition with Sign Restrictions

This section provides details on the decomposition of broad financial shocks using sign restrictions presented in Section 4.2.

Let $M \equiv \begin{bmatrix} \boldsymbol{v}_{\mathrm{F}} & \Delta\boldsymbol{\rho} \end{bmatrix}$ denote the observed series, $U \equiv \begin{bmatrix} \boldsymbol{v}_{\mathrm{F,purged}} & \boldsymbol{v}_{\mathrm{F,res}} \end{bmatrix}$ denote the structural shocks for which $U'U$ is a diagonal matrix, and C denote the sign restriction matrix. Equation (7) is thus summarized as

$$M = UC. \tag{24}$$

To identify the set of matrices C that satisfy the sign restrictions, we implement sign restrictions using the Givens rotation and the so-called "poor man's sign restrictions."[18] We use the Givens rotation as our baseline approach, and results are little changed under the alternative.

Givens rotation matrices. As in Jarocinski (2020), we construct the structural shocks, U, and the impact matrix, C, as

$$U = QPD \text{ and } C = D^{-1}P'R, \tag{25}$$

where Q is an orthogonal matrix based on QR decomposition of the observed series M, P is a rotation matrix, and D is a scaling matrix to ensure that decomposed shocks add up to the broad financial shocks.

Each matrix in (25) is constructed as follows. We first use the QR decomposition to decompose M into two orthogonal components:

$$M = QR, \quad \text{where } Q'Q = I_2, \text{ and } R = \begin{bmatrix} r_{11} > 0 & r_{12} \\ 0 & r_{22} > 0 \end{bmatrix}. \tag{26}$$

[18] The Householder's transformation is another common approach in estimating the set of matrices C, which Fry and Pagan (2011) show to be equivalent to the Givens rotation.

Then we rotate the orthogonal components with the matrix P, defined as

$$P = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \quad \text{for } \theta \in [0, 2\pi]. \tag{27}$$

Sign restrictions are imposed on elements of the unscaled impact matrix, $P'R$. The set of angles θ that satisfies sign restrictions is

$$\theta \in \{(0, \arctan\frac{-r_{22}}{r_{12}}) \text{ for all } r_{12} < 0\} \cup \{(\arctan\frac{r_{12}}{r_{22}}, \frac{\pi}{2}) \text{ for all } r_{12} > 0\}. \tag{28}$$

Finally, we scale the set of structural shocks that satisfy sign restrictions, QP, by a diagonal matrix D to ensure that they add up to the broad financial shocks. D is specified as

$$D = \begin{bmatrix} r_{11}\cos\theta & 0 \\ 0 & r_{11}\sin\theta \end{bmatrix}. \tag{29}$$

The set of decomposed shocks, U, is set identified. We follow Fry and Pagan (2011) and use the median shocks among the set of admissible shocks as $v_{\mathrm{F}t,\mathrm{purged}}$ and $v_{\mathrm{F}t,\mathrm{res}}$.

The poor man's sign restrictions. As another robustness, we perform a simple decomposition using "the poor man's sign restrictions" proposed by Jarociński and Karadi (2020). A broad financial shock, $v_{\mathrm{F},t}$ is classified as a purged financial shock if the broad financial shock and EBP changes are negatively correlated, i.e., $v_{\mathrm{F},t} \cdot \Delta\rho_t < 0$. Otherwise, if the broad financial shock and EBP changes are positive correlated, then the shock is classified as a residual component. Under this method, a given broad financial shock is classified as either $v_{\mathrm{F}t,\mathrm{purged}}$ or $v_{\mathrm{F}t,\mathrm{res}}$, but not both. In contrast, a given broad financial shock can contain both types of shocks under the Givens rotation.